# THE EFFECTS OF DUAL CREDIT ENROLLMENT ON SECONDARY AND HIGHER EDUCATION OUTCOMES: THE UTAH CASE

by

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# ABSTRACT

Based on the premise that increases in productivity are, in part, a function of higher education performance and improved secondary education output, this study considers the various public education career paths available to Utah public high school students, and examines the effects each have on secondary education performance and graduation, and postsecondary higher education enrollment, time-to-completion, and degree attainment for the Utah public high school graduation cohorts of 2008 and 2009.

The focus of this paper is an examination of the Utah Data Alliance longitudinal data set compiled by in cooperation with the Utah Education Policy Center, Utah Education Network, Utah College of Applied Technology, Utah State Office of Education, Utah System of Higher Education and Utah Department of Workforce Services. This data set allows for individual level examinations of Utah public education students throughout their public education careers and into the workforce.

The data examination and estimated outcomes are driven by the use of Propensity Score Matching in an effort to limit the endogeneity and self-selection bias present in nonexperimental, observed data samples. The quasiexperimental design structure of this method provides a path towards the assignment of causality. Though Propensity Score Matching offers such a pathway, as an estimator its strength is reliant

on the existence of complete and quality matching variables, which are limited in the Utah education longitudinal data sets.

Taking participation in Dual-Credit Enrollment and Early College High School as reforms in secondary, applied as treatments on student populations, and matching students by demographic and performance criteria prior to the treatment application, we're able to estimate the average treatment effects on the treated of the two reforms separately and collectively. The estimated outcomes on secondary education standardized testing and graduation, and postsecondary higher education enrollment and degree attainment are positive or reflect positive effects for each of the examined student populations. Of particular interest, however, is the scale of the effects on the various secondary and higher education outcomes and what this may yield with respect to public education policy.

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At first, I may not appear a likely champion of heterodox economics. Having enjoyed a career in financial services and business ownership, I chose to pursue an advanced degree in economics at the University of Utah not because of its reputation as a leader in heterodoxy, but in spite of it. While most consider such an education to be steeped in leftist thought, I've come to realize heterodoxy as holistic rather than leftward leaning. Through Marx I've come to understand the language of Capitalism, Polanyi aided in my awareness of the strengths and weaknesses of labor and commodities, Kaldor and Kalecki taught me about the dynamics of systems and their sometimes sensitive response to change, and from Keynes I've gained an appreciation of when governments should resist the temptation to intervene in markets and to respect the courage and vibrancy of Hayek.

I could easily include the names of some of the extraordinary instructors from whom I've gleaned both content and context rather than those of Economics theorists, but it would make them uncomfortable and I've come to respect and admire them too much to do so. This group not only includes my professors, who've been sufficiently committed to my education to argue with me, criticize me, question my thinking and remind me of the import of heteroskedasticity, but also of my peers. Through their eyes I've seen wonders I'd never imagined and traveled through ideologies and places

previously beyond my vision. To suggest that I am grateful would be to vastly understate how I've come to personally and professionally value them.

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While many graduate students make their way through academia prior to establishing careers and families, I chose to step into the demands of a PhD program while my children pursued their own undergraduate and graduate careers, and began to form and raise their own families. While the time demands have made some aspects of our relationships challenging, the coincidence of our academic experiences has ironically and unexpectedly added common ground and experience to already close relationships. Though the opposite may be said for my sweet wife, Leslie, with our lives diverging at the very time in life during which most couples begin to enjoy greater levels of leisure and renewed common interests. Her trust and support have often been the motivating factors for my focus and determination, as it has been for more than 30 years. I adore them all and am grateful for their love and support.

I was recently called a liberal by one who for whom the label is distasteful. But in the American sense, where liberal is meant as leftward leaning, I am anything but. What I've come to realize is that the many influences and institutions helping to form my thoughts and expectations have motivated a level of pragmatism and liberality not at all inconsistent with each other, nor with the rational and sometimes conservative social and political openness I enjoy.

# 1. INTRODUCTION

As recently as the late 1950s economists began to formulate a theory of human capital as an input to production separate from physical capital and beyond the limits of the contribution of the size of the labor force alone. "What is the contribution of changes in the quality of people to economic growth?" (Mushkin, 1962, p. 129) questioned Selma Mushkin, coincident with research findings published by University of Chicago' s Theodore W. Schultz (1961) and Gary Becker (1962), and on the heels of two important international conferences on investment in people as a facet of economic development (WHO, 1961). The work of these scholars, their collaborators, and peers framed much of the political economy, motivations, and foundational elements for human capital policy initiatives that would define the latter part of the 20$^{th}$ Century.

In the intervening decades it has become generally accepted that increased investments in human capital yield productivity gains resulting in higher per capita and aggregate incomes, and that these investments are observable primarily through investments in education and healthcare.[1] Economic theorists have presented and continue to develop rigorous models in testing various hypotheses, with the resulting analyses offering support towards increased human capital investment the world over

[1] A third element of human capital investment includes investments in migration or labor mobility. This issue is not specifically addressed in this research, but it is important to note that investments in migration plays an important role in productivity and income at the individual and societal levels.

(Becker, 1962; Goldin & Katz, 2005; Nehru, Swanson, & Dubey, 1993; Schultz, 1961). Twentieth-century domestic policy makers intent on fulfilling an expanding social contract, leveraging a rapidly evolving postwar workforce, and securing productive domestic gains have pursued initiatives in support of increased investments in education and healthcare, human capital's primary inputs, sufficient to facilitate a golden age for western capitalism and secure America's ascendency as a global leader in innovation, productivity and lifestyle. Through the mass adoption of public education and expansion of healthcare programs, public policy makers successfully pursued an agenda in support of people as net contributors to society and inputs in production (Decker, Moore, Rice, & Rollefson, 1997; Easterlin, 1981; Grossman, 1972; Grossman & Helpman, 1993).

Perhaps no other debate has greater potential impact on future productivity, economic growth and social welfare than does that of how our society will allocate and pay for investments in human capital. In the highly developed and globally interdependent economy of 21$^{st}$-Century America, state and enterprise level policy initiatives address the future well-being of society, including its costs, to whom and at what level resources should be made available, and the impact of a more highly educated population on American productivity, innovation and personal satisfaction. The cost, quality, and availability of primary, secondary, and higher education are integral elements shaping domestic productivity, individual level satisfaction and America's competitive position as a leader in innovation, economic growth, and individual level standards of living.

## Problem Statement

In developed nations, the United States in particular, increased investments in education have more recently provided sometimes inconsistent and ambiguous results, suggesting that the marginal return may not be sufficiently positive to justify the expenditure: Further general investments may not provide the necessary returns (Nehru, 1993). However, as changes in per pupil investments in education are observed in the United States the effects are generally statistically significant and positively correlated, indicating that changes in these investments result in similarly signed changes in the measured outcomes (Goldin & Katz, 2005). The net effect of these findings offers at least two possible conclusions: 1) While the effect of increased investments in education may not be sufficiently positive to justify the expenditure, they may be necessary to maintain the nation's already relatively highly skilled human capital stock, and 2) the national education infrastructure is brittle and subject to a human capital depreciation effect absent sustained levels of per pupil investment.

The rising costs of these inputs to human capital, coupled with growing national interest in fiscal responsibility and widening relative socio-economic distributional inequalities, renders the need for innovative solutions in support of efficient and improving outcomes.

## Potential Expectations, Solutions and Methods

Dual-credit enrollment programs have become widely popular in the United States, possibly motivated by a set of expected outcomes among students, parents, educators and policy makers. The potential for earning higher education course credit while in high school may motivate expectations of higher rates of high school graduation, higher education enrollment, completion and possibly even improved time-to-completion as students become so invested in their educations (Berger, Turk-Bicaki, Garet, Song, Knudsen, Haxton, Zeiser, Hoshen, Ford, & Stephan, 2013; Speroni, 2011; Swanson, 2008). Further, where the expense of these higher education credits earned while in high school are borne by the public school system, students and households may have come to expect higher education cost decreases, possibly led by decreased time-to-completion (Kearl, 2012; Swanson, 2008).

Though there are variations from state to state, these programs allow secondary education students to earn higher education credits through taking high school courses that fulfill college level requirements. These programs, available in public education systems in virtually every state, offer some evidence of easing the transition between high school and college generally (Aldeman, 1999; Bailey, Hughes, & Karp 2003; Speroni 2011; Struhl & Vargas 2012) and motivate improvements in secondary and higher education outcomes (Swanson, 2008). While participation relies heavily on guidance offered students by high school faculty and staff, from within the student's household and social structures, and the individual ambitions of students, many of the effects of participation are observable, statistically significant, and largely positive (Swanson, 2008). This is not intended to suggest that the entire range of effects of these programs are consistently positive, as every gain comes at a cost, but that many stake holders in these systems have developed high expectations of their effects on certain outcomes. This study focuses on some of those outcomes in an effort to quantify the effects and determine whether or not the noted expectations are warranted.

Early College High School, a focused form of dual-credit enrollment, provides a structure through which students are focused towards earning a substantial number of higher education credits while in high school, often sufficient to earn an Associate's Degree, rather than simply earning a high school diploma and a limited range of higher education credit (Early College Initiative).[2] Both programs are intended to provide a head start towards college completion at the expense of the state's public education system and without greater burdens on that system or those households supporting it (Fincher-Ford, 1996; Karp & Hughes, 2008; Welsh, Brake & Choi, 2005).

Like the United States, Utah has traditionally enjoyed such educational output as to place it amongst the top of its peer group, but that position has eroded in recent decades and improvements are being called for from both the public and private sectors.[3] The formation of Utah Data Alliance (UDA[4]), enabled by funding from the

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[2] The Early College Initiative; http://www.earlycolleges.org/. Early College High Schools are small schools from which students leave with not only a high school diploma but also an Associate's Degree or two years of college credit. By changing the structure of the high school years and compressing the number of years to college degrees, Early College High Schools have the potential to improve graduation rates and better prepare students for entry into high-skill careers. This approach helps people acquire the education and experience they need to succeed in life and a family-supporting career. The Bill and Melinda Gates Foundation, along with Carnegie Corporation of New York, the Ford Foundation, and the W.K. Kellogg Foundation, are funding the Early College High School Initiative. Over 5 years, the initiative will create or redesign 150 Early College High Schools for underserved and low-income young people and neighborhoods. Jobs for the Future coordinates the initiative.

[3] Utah's public-private sectors partnered to form ***Prosperity 2020***, a privately funded effort to improve educational output and household productivity in response to the state's intent improving its overall competitiveness.

[4] Utah Data Alliance (UDA) is a partnership of agencies in Utah formed to create tools to facilitate data-driven decision making for school and district improvement, and to provide educators and other decision

American Recovery and Reinvestment Act of 2009 (ARRA[5]) and the Utah Legislature (2014[6]), facilitated the compilation of a longitudinal data set of Utah public education data sufficiently rich to examine the effects of Dual-Credit Enrollment and Early College High School on the targeted secondary and higher education outcomes. The data include individual level student data from the Utah State Office of Education (USOE),[7] Utah System of Higher Education (USHE),[8] Utah College of Applied Technology (UCAT)[9] and Utah Department of Workforce Services (UT DWS)[10] inclusive of public education enrollment, performance, and completion data, and limited demographic, labor market and income data. To date, access to this data has been restricted to the Utah Data

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makers with the historical timely and vital evidence they need to raise individual student achievement and close achievement gaps. http://www.utahdataalliance.org/

[5] The American Recovery and Reinvestment Act of 2009 (ARRA, Pub. 111–5), commonly referred to as the *Stimulus* or *The Recovery Act*, was an economic stimulus package enacted by the 111th United States Congress in February 2009 and signed into law on February 17, 2009.

[6] Utah Senate Bill 0034 (March 2014) provided ongoing funding for the Utah Data Alliance and Utah Education Policy Center http://le.utah.gov/~2014/bills/static/SB0034.html

[7] Utah State Office of Education (USOE) reports on a wide range of data related to public education in the state (http://www.schools.utah.gov).

[8] The Utah System of Higher Education (USHE). Established in 1969, USHE is comprised of eight public colleges and universities, governed by the State Board of Regents and assisted by local Boards of Trustees. The system is comprised of two research universities: the University of Utah and Utah State University; one liberal arts and sciences university: Southern Utah University; three regional universities: Weber State University, Dixie State University, and Utah Valley University; and two community colleges: Snow College and Salt Lake Community College (www.higheredutah.org).

[9] UCAT is a system of technical colleges located throughout Utah known as Applied Technology Colleges (ATCs). Established by the State of Utah, UCAT provides market-driven technical education through the eight ATCs that meets the needs of Utah's employers for skilled workers.

[10] Utah Department of Workforce Services supports Utah’s vision to strengthen the state and local economies by supporting the economic stability and quality of our workforce (www.jobs.utah.gov).

Alliance partners, including researchers associated with the Utah Education Policy Center (UEPC[11]).

A number of studies consider outcomes for participants in Dual-Credit Enrollment and Early College High School programs (Karp, Calcagno, Hughes, Jeong & Bailey, 2007; Kim & Bragg, 2008; Speroni, 2011; Struhl & Vargas, 2012; Swanson, 2008), but few employ statistical methods sufficient to infer causality and to estimate their effects (An, 2009; Taylor, 2013; Speroni, 2011; Struhl & Vargas, 2012). Propensity Score matching (PSM) is among the credible processes developed via methodological advances in social sciences research offering alternatives to linear regression models (Austin 2011; Dehejia & Wahba, 2002; Peikes, Moreno & Orzol, 2012; Rosenbaum & Rubin, 1983). The methodology aims to reduce observable bias, including self-selection bias, and produce more credible estimates of average treatment effects than regression analysis in nonexperimental studies.

Propensity score matching considers a population inclusive of observations of relevant subject data before and after a given treatment. Through the assignment of a propensity score, based on a set of demographic and pretreatment performance variables through which participants are matched, the method estimates the average treatment effect (ATE) on the sample population, as well as the average treatment effect on the treated (ATET) within that population. The method's reliance on matching subjects based on available observed data renders it useful as an instrument in support

[11] The Utah Education Policy Center (UEPC) is an independent, nonpartisan University of Utah research center in the College of Education that bridges research, policy, and practice for Utah public schools and higher education (www.uepc.utah.edu). The center houses the Utah Data Alliance and other research and policy based projects.

of offering causal inference, but that inference is only as credible as the completeness and accuracy of the data (Eide & Showalter, 2012; Murnane & Willet, 2011; Schneider, Kilpatrick, Schmidt & Shavelson, 2007).

## Research Focus

The focus of this research is to analyze the secondary and higher education effects of two particular reforms in secondary education, Dual-Credit Enrollment and Early College High School, as applied to Utah's 2008 and 2009 public high school graduation cohorts. This is accomplished through the use of Propensity Score Matching in an examination of the Utah Data Alliance longitudinal dataset. The study includes select demographic and public education enrollment and performance data and specifically considers the effects of participation in Dual Credit Enrollment and Early College High School programs on secondary education performance (ACT scores) and graduation, postsecondary higher education enrollment, and higher education time-to-completion with respect to Associate's and Bachelor's Degree completion and degree attainment. Dual-Credit Enrollment and Early College High School are, in effect, treatments selected by certain public high school students, with Traditional high schools students being the control, or nontreated, group.

Of particular concern when examining the effects of such programs is the estimation bias resulting from endogeneity and self-selection. As the data are nonexperimental, observational data, endogeneity bias and confounding variable relationships are unavoidable. To minimize these endogeneity effects this study's use of Propensity Score Matching's methodology matches each observation with one other wherein like groups of students, based on select demographic and education performance criteria, are matched prior to treatment selection such that the average treatment effects on the treated (ATET) are observable for those treated versus those who are not.

Propensity Score Matching analytics are not strictly regression estimates. Rather, the method creates a propensity score representing the probability of a subject's inclusion in the treated group and then computes a coefficient representing the treatment effect on the measured. If the outcome is continuous, the effect of treatment is estimated as the difference between the mean outcome for treated subjects and the mean outcome for untreated subjects in the matched sample (Rosenbaum & Rubin, 1983). If the outcome is binary, the effect of treatment is estimated as the difference between the probability of subjects experiencing the event in each of the two groups (treated versus untreated) in the matched sample. Thus, the reporting of treatment effects can be stated in similar metrics as those that are commonly used in randomized control treatments. The estimates report with coefficient, standard error, *P* value, and confidence intervals as do regressions estimates, but include a calculated *z* score rather than *t* statistic to aid in inferring statistical significance and do not include an *r* squared value suggestive of the level of the of the model's fit.

As outcomes based on propensity score matching methods may vary depending the selection of pretreatment variables and on adjustment mechanisms internal to the methodology's models (nearest neighbor, caliper, tolerance, form), Receiver Operating

Characteristic (ROC) Analysis is used in this study to identify and employ the most accurate model given the available variables and possible adjustments. Receiver Operating Characteristic Analysis quantifies the accuracy of diagnostic tests or other evaluation modalities used to discriminate between two states or conditions, allowing the discriminatory accuracy of a diagnostic test to be measured by its ability to correctly classify known subjects (Eng, 2005; Fawcett, 2006; Metz, 1978).

## Research Aims

The aim of this study is to offer a view of Dual-Credit Enrollment and Early College High School as reforms in secondary and higher education towards sharpening respective public policy initiatives affecting their use, funding, and outcomes. As public education programs, these reforms are supported through taxpayer resources, presumably motivated by expectations of improved secondary and higher education performance at the micro and macro levels. While there is some evidence that these programs motivate certain improved outcomes (Karp et al., 2007; Kim & Bragg, 2008; Speroni, 2011; Struhl & Vargas, 2012; Swanson, 2008,), there is virtually no evidence with respect to the effect of these programs for Utah public high school students, their households, and the public funds on which they rely. This study intends to offer a view of the effects these programs have on select student outcomes, and how these effects and outcomes may be considered with respect to Utah public secondary education generally, and for Utah's underrepresented students specifically.

## Research Questions

This research effort expressly seeks to consider the effects of student participation in Dual-Credit Enrollment and Early College High School programs on public high school performance graduation, public higher education enrollment and completion, time-to-completion and degree attainment. The broader questions under consideration are:

1. What are the effects of Dual-Credit Enrollment and Early College High School on Utah's public education general student populations with respect to high school performance and graduation, and higher education enrollment, completion, time-to-completion, and degree attainment?
2. What are the effects of Dual-Credit Enrollment and Early College High School on Utah's underrepresented public education population with respect to high school performance and graduation, and higher education enrollment, completion, time-to-completion, and degree attainment?

## Research Significance

The two research questions posed are closely related and the answers to each may offer important insights with respect to the potential fulfillment of expectations of Dual-Credit Enrollment and Early College High School programs. As noted in the Research Focus section of this study, there are been few studies of dual-credit programs employing statistical methods capable of supporting credible causal inference and none has considered differentiating the effects of Dual-Credit Enrollment from those of Early College High School. Additionally, there are no empirical studies considering the effects of these programs in the State of Utah. Finally, this study represents the first individual level examination of the Utah Data Alliance longitudinal data sets performed by a researcher from outside of the Utah Data Alliance and its partners.

## Definitions

*Charter Schools*: Charter Schools are public schools organized through the efforts of state charter school boards, parents, and educators (Finn, Manno, & Bierlein, 1996). These schools are held to the same funding mechanisms as are all public primary and secondary schools and are open to all public education participants within their respective boundaries. The majority of charter schools are overseen by a board of trustees comprised of parents, educators, and other interested parties, while some Charter Schools are managed by private charter school operators.

*Cohort Graduation Rate*: The 4-year adjusted cohort graduation rate is used by the US Department of Education (US Department of Education, 2008) and in this study with respect to public high school graduations, herein referred to as the *Cohort Graduation Rate*. This rate includes the “number of students who graduate from high school in four years with a regular high school diploma divided by the number of students who form the adjusted cohort for the graduating class” (US Department of Education, 2008, p. 2). This differs from what many commonly consider a high school graduation rate, which may be calculated as simply as the number of high school graduates in a particular class divided by the number of students in that class. Such a calculation commonly results in a generalized graduation rate rather than the cohort graduation rate.

*Dual credit enrollment*: The term *dual credit enrollment* is used generally and specifically throughout public and private secondary education literature (Clark & Cambra, 2001; Speroni, 2011; Waits, Setzer & Lewis, 2005). In this study I differentiate *dual-credit enrollment* versus *Dual-Credit Enrollment* with the former intended to represent any secondary education effort through which high school and higher education course credits may both be earned simultaneously. *Dual-Credit Enrollment* is used to represent programs allowing for these credits to be earned specifically while enrolled in a traditional public high school setting. In this sense, dual-credit enrollment includes Dual-Credit Enrollment and Early College High School. Generally, dual credit enrollment courses include concurrent enrollment, advanced placement (AP), early enrollment, and college level examination program (CLEP), regardless of the setting in which they're earned.

*Early College High School*: Early College High School is a specific form of public secondary education in which participants attend public high school on or near an accredited college campus, typically a community college (Berger et al., 2013). The curriculum is designed in such a manner as to promote the earning of a higher education Associate's Degree coincident with receiving a high school diploma, and as such, many of the courses offered are varying types of dual-credit enrollment courses. In Utah, all Early College High Schools are Charter Schools,[12] though this is not the case throughout the nation.

[12] Utah Charter School Board http://www.schools.utah.gov/charterschools/default.aspx

*High school graduation cohort*: A high school graduation cohort consists of those students enrolled in high school such that they're expected to graduate in the late spring of the particular cohort year. This includes students who drop out, graduate early, elect to earn a general education development diploma (GED), as well as those who graduate from high school with a traditional diploma. In this study, the high school graduation cohorts of 2008 and 2009 are examined and include only those individuals enrolled in public secondary education in the state of Utah.

*Public high school*: Public high school includes those secondary education institutions subject to their respective states offices or departments of education. This includes, but is not necessarily limited to, traditional high schools, alternative schools, charter schools, and Early College High Schools.

*Traditional*: the term Traditional is used in this study to include public high school students who attend a traditional public high school, usually designated via geographic boundary, without participating in dual-credit enrollment programs of any kind. The term is intended to differentiate these students from those who enroll in Dual-Credit Enrollment courses while attending a traditional public high school or Early College High School.

*Treatment*: Dual-Credit Enrollment and Early College High School are considered as self-selected Treatments applied to students in the respective high school graduation cohorts. This study considers the effect of these treatments separately (DCE, ECHS), and collectively (General or Combined).

*Underrepresented students*: For the purposes of this study, students for whom high school and higher education participation, performance and completion statistics have been lower than the aggregate statistics are considered underrepresented students. This is consistent with the use of the term throughout available literature and includes students classified by gender, race/ethnicity, income, mobility, and primary language.

## 2. CHALLENGES AND TRENDS IN SECONDARY AND HIGHER EDCATION

Education research in recent decades has revealed troublesome trends in public education: That of lower-than-expected and stagnating high school graduation rates between 1970 and 2000 (Heckman & LaFontaine, 2010; NCES[13], 2011; Vargas 2013), increasing need for remedial education at the postsecondary levels (Aldeman, 2010; NCES, 2013), and declining higher education completion rates (Cook & Pullaro, 2010). Through national education data reports (NCES, 2011) we see that public high school graduation rates reached a peak of 78.7% in 1969-1970, steadily declined to 69.3% in 1994-1995, stagnated towards 69.8% in 1999-2000, and have since begun to recover, climbing back towards the 1969-1970 peak coincident with the advancement of reforms in secondary education. However, not all student populations have enjoyed this recovery. Heckman and LaFontaine (2010) established that underrepresented student differentials are substantial and have not converged towards those of the general student population for more than 35 years. Just as concerning is the rising need for remedial education among the nation's high school graduates/higher education enrollees with nearly half of all postsecondary students need at least one remedial course upon entering college (Aldeman, 2010; Li, 2011). Finally, Cook and Pullaro (2010)

[13] National Center for Education Statistics, Digest of Education Statistics 2011: http://nces.ed.gov/programs/digest/d11/tables/dt11_111.asp

note that while higher education enrollment has increased in recent decades, completion rates have steadily declined.

Stagnating high school graduation and increasing higher education remedial education needs are reflective of lower than expected levels of college readiness among American youth as too many students are unprepared for enrollment and success in college and university level courses (Venezia, Callan, Finney, Kirst & Usdan, 2005). Separately and collectively this lack of readiness translates into lower levels of productivity at the individual, household and state levels (Aldeman, 2010; Greene & Forster, 2003), levels necessary in maintaining global competitiveness and incomes for all socio-economic groups. Whereas human capital investments in secondary education provided positive and significant results in the Unites States during the high school movement of the mid-20$^{th}$ century (Goldin & Katz, 2005), such investments in the intervening period have resulted in ambiguous outcomes for many student populations.

Further, low rates of higher-education degree attainment and rising time-to-completion reflect a national problem in respect to temporal and fiscal resources expended at the college level in support of remedial coursework (Vargas, 2013). The situation is particularly acute for low-income, minority and other underserved youth representing the fastest growing public education populations in the country, and with some of the lowest success rates in K-12 and postsecondary education systems. "Every student who falls short of the goal of earning a high school diploma and a college degree represents a financial investment that did not pay off in a credential of value in the labor market" (Vargas 2013, p. 1). Over 50% of students entering 2-year colleges and nearly

20% of those entering 4-year universities are placed in remedial classes and 65% of low income students in 2-year colleges take at least one remedial course; some 22% do so in 4-year colleges (Complete College America, 2012).[14]

Nationally, more than 7,000 students become dropouts every school day, adding up to over 1 million students annually who will not graduate from high school with their peers as scheduled (Editorial Projects in America, 2010). For years, researchers have called attention to the national dropout crisis in an effort to create federal, state, and local policy that addresses the issue.

Despite years of research and a growing consensus that something must be done to confront the crisis, the nation's high school graduation rate has largely remained flat (Alliance for Education, 2011). Seventy-nine percent of high school students across the country graduate from high school on time with a regular diploma (US Department of Education, 2008), while the remaining twenty-one percent, an estimated 1.3 million students from the nation's Class of 2010, failed to graduate with their peers (Alliance for Excellent Education, 2011).

In a time of constrained resources and a growing sense of urgency over the need to improve and increase primary, secondary and higher education outcomes and degree completion, the nation's secondary and postsecondary education systems need better ways to document both programmatic and cost effectiveness (Baum, Ewen, Long,

[14] Complete College America, 2012 ; Complete College America is a national nonprofit with a single mission: to work with states to significantly increase the number of Americans with quality career certificates or college degrees and to close attainment gaps for traditionally underrepresented populations: http://completecollege.org/about-cca/

Mattoon, McClenney, Mehaffy, Middaugh, Paulson, Redd, Somerville, & Williams, 2009). At the same time, the tool kit of effective interventions for addressing the dropout crisis at the student and school levels is growing. Across the board, educators and policy makers agree that among the most productive and efficient ways of bringing about improved rates of return on higher education includes improved preparation in public secondary education, particularly public high school education, towards college readiness and improving transitions between secondary and postsecondary education participation.

No longer are these simply anonymous students; compared to a decade ago, much more is now known about both the nongraduating students and the high schools from which they come. The US Department of Education and its research agency, The National Center for Education Statistics[15] have cultivated two longitudinal education studies - the National Education Longitudinal Study[16] (NELS 88:2000) and the Education Longitudinal Study[17] (ELS 2002) – and the American Reinvestment and Recovery Act of 2009 (ARRA 2009) provided funding to 28 states to cultivate individual level state education longitudinal studies. Together, these and other rich data resources have facilitated a growing body of research demonstrating that it is possible to track

[15] The National Center for Education Statistics (www.nces.ed.gov) sponsors an expanding body of research on a broad range of domestic education and public policy related issues, including sponsoring the National Education Longitudinal Study (NELS 88:2000) and the Education Longitudinal Study (ELS 2002).

[16] National Education Longitudinal Study (NELS 88:2000) is a detailed statistical survey of the high school cohort of 1988, inclusive of four rounds of follow up, the latest of which was conducted in 2002: nces.ed.gov/surveys/nels88/

[17] The Education Longitudinal Study of 2002 (ELS 2002) is the second education longitudinal study sponsored by the National Center for Education Statistics and adds to the national statistical data resource formed by the completion of the NELS 88:2000: nces.ed.gov/surveys/els2002/).

individual students and predict who is likely to drop out of high school, as well as the high schools and program types most likely to generate the greater part of the nation's dropouts (Alliance for Excellent Education, 2008). This research discusses targeted interventions to improve secondary education outcomes generally and bring students who are at risk of dropping out back on track to graduation.

Not only is such preparation important generally, but the changing face of American business, our dependence on global market structures, and a critical need to aid in the evolution of the nation's lower-skilled workforce into a more highly productive, highly skilled workforce capable of filling positions reflective of high levels of human capital investment has become key in furthering domestic economic growth and development.[18] As of 2018 the nation will need 22 million more students to earn a college degree in order to staff these positions, but America is expected to fall short of this goal by at least 3 million (Carnevale, Smith, & Strohl, 2010). This study echoes past work by Thomas Bailey, professor of economics and education at Columbia University and director of the National Center for Postsecondary Research, who sounded a similar warning to improve education attainment rates, particularly among students of color, in order to be prepared for the workforce demands of the future (Bailey, 2007).

The US Department of Labor estimates that 90% of the jobs in the fastest-growing sectors of the economy will require some postsecondary education. One estimate places the number of unfilled jobs arising from insufficient skills level of the US

[18] Comments offered by Margaret Spellings to the US Chamber of Commerce Foundation: http://education.uschamber.com/press-release/us-chambers-report-highlights-essential-role-businesses-play-improving-stem-education

human capital stock in July 2013 at 3.7 million jobs and warns that by 2020 employers across the globe stand to face a skills shortage of as many as 85 million workers (Carnevale, Smith, & Strohl, 2010). The US Department of Commerce estimates that STEM jobs will grow by 17% between 2008 and 2018, compared with just 9.8% growth in non-STEM jobs. However, at the current pace, the United States simply will not produce enough workers to fill the jobs (BLS, 2013; Hess, Kelly, & Meeks, 2011). It is no wonder, then, that business groups are calling for higher rates of secondary and postsecondary graduation, more affordable college education, and higher levels of degree attainment, particularly in the important STEM areas (Hart Research, 2013).

**Benefits of Improved High School and Higher Education Performance**

Growing research supports the notion that better educational outcomes lead to greater economic returns including recent studies examining four major connections between education and the economy: the economic benefit to individuals by improving their own educational attainment; the economic costs of low education attainment rates, primarily through increased public expenditures such as Medicaid or welfare for those with lower education levels; the role of education in ensuring the nation can fulfill future workforce demands and remain globally competitive; and the positive link between improved education and the nation's economic growth. The aim then is to make meaningful improvements in these areas, but to do so in such a way as to motivate more efficient outcomes through existing resources rather than to simply increase investments in potentially less efficient programs and technologies.

Graduating just half of the dropouts from the Class of 2010 would have resulted in significant economic benefits to the nation, including billions in increased annual earnings and the creation of 54,000 new jobs. In addition to the moral imperative to provide every student with an equal opportunity to pursue the American dream, there is now an economic necessity for helping more students graduate from high school. In the knowledge-based economy of the 21st century, education is the main currency (Alliance for Excellent Education, 2011).

Research suggests that improving education could have the power to grow the economy by boosting the gross domestic product and creating jobs. In 2009, McKinsey released an often-cited report (McKinsey, 2009) likening low levels of academic achievement and attainment to a permanent national recession. In the report, the authors assert that if the United States had improved its educational achievement levels to those of the world's leaders in education the nation's GDP could have grown by as much as $2.3 trillion, or 16%. In addition, a 2002 review of economic literature conducted by Yolanda Kodrzycki of the Federal Reserve Bank of Boston (Kodrzycki, 2010) concludes that increases in labor quality via educational attainment have had a measurable effect on economic growth in recent decades. Similarly, in the Organisation for Economic Co-operation and Development's 2010 report, *The High Cost of Low Educational Performance: The Long-Run Economic Impact of Improving PISA Outcomes*, the authors conclude that any improvement in the knowledge and skills of a nation's workforce are an important force in economic development (OECD, 2010). As such, an investment in improving education outcomes is important for a nation's economic development.

If just one half of the 1.3 million students who dropped out of the nation's Class of 2010 had graduated, together those new graduates would likely have earned up to $7.6 billion more each year than what they will likely earn without a high school diploma (Alliance for Excellent Education, 2011). These increased earnings would have rippled throughout the economy and created additional economic benefits, including the following:[19]

- Increased spending and investment: New graduates' increased earnings, combined, would likely have allowed them to spend up to an additional $5.6 billion and invest an additional $2 billion during an average year.
- Increased home and vehicle sales: By the midpoint of their careers, these new graduates would likely have spent as much as $19 billion more on home purchases than they will likely spend without a diploma. In addition, they would likely have spent up to an additional $741 million on vehicle purchases during an average year.
- Job and economic growth: The additional spending and investments by these new graduates, combined, would likely have been enough to support as many as 54,000 new jobs and increase the GDP by as much as $9.6 billion by the time they reached their career midpoints.

[19] The data sources and methodology used in calculating economic benefit projections are available at http://www.all4ed.org/files/EconTechNotes_leb_seb.pdf.

- Increased tax revenue: As a result of these new graduates' increased wages and higher levels of spending, state tax revenues may have grown by as much as $713 million during an average year.
- Increased human capital: 43% of these new graduates would likely have enrolled in a postsecondary program after earning a high school diploma. However, only 170,000 of them, or 27% of all new graduates, would be expected to complete a postsecondary credential, including a vocational certificate, a 2- or 4-year degree, or a higher achievement, which signals a gaping hole in the secondary-to-postsecondary pipeline.

Improving outcomes, particularly for low-income students, increases the productivity of taxpayer investments in education (Vargas, 2013). Nationally, only 65% of low-income students who start eighth grade complete high school, compared with 87% of their higher income peers. If the state could raise the high school graduation rate of low-income students to that of their higher-income peers, it would increase productivity of education investments by lowering the cost of high school completion by $1,371 per graduate. The gaps are even larger when it comes to higher education. Only 17% of low-income students entering public high schools earn a higher education degree; compared with 57% of their higher-income peers. Closing the income-related gap in college completion would increase the productivity of public investments by $1,452 per Associate's Degree and by $3,607 per Bachelor's Degree. Increasing the college-readiness rates for low-income students by 20% could lower the cost per Associate's Degree by as much as $1,148 in higher spending states through decreased expenditures on remedial education too often required at the college level. Together, these savings for higher-spending states, such as Texas, California and New York, can lower the cost-to-completion by as much as $4,711 per Associate's Degree and $4,194 per Bachelor's Degree (Vargas, 2013).

The Alliance for Excellent Education[20] refers to state level funds spent towards improving high school graduation as "the best economic stimulus package" possible for an economy considering increasing expenditures in an effort to raise state and individual level incomes (Alliance for Excellent Education, 2012). On average, a high school graduate nationally earns $7,840 more than a high school dropout; in Utah that figure is $7,536.[21] If just half of high school dropouts graduated, the added economic benefit would amount to a multibillion dollar stimulus package directed towards that portion of the society most likely to participate in costly social programs, resulting in the following economic benefits to the US and Utah, respectively (Alliance for Excellent Education, 2011).

## Reforms in Search of Efficient and Productive Outcomes

As noted, improving outcomes for US high school students may correlate to improved social and economic conditions generally, but such improvements require innovation and creativity rather than simply increasing the level of investment. Reflective of such reforms is the increase in the availability of higher-education-credit-

[20] The Alliance for Excellent Education is a Washington, DC-based national policy and advocacy organization that works to improve national and federal policy so that all students can achieve at high academic levels and graduate from high school ready for success in college, work, and citizenship in the 21st century. http://all4ed.org/about/

[21] Source: US Department of Education

based programs throughout the nation's public high schools, which programs result in improved levels of college readiness. These programs are offered by both secondary and postsecondary institutions and have been designed to meet a broad range of needs (Bailey & Karp, 2003; Swanson, 2008). In addition to providing a more rigorous curriculum, they also seek to provide a lower cost method of obtaining higher education credits, thus reducing overall college costs. Traditional programs include those programs that are exam based such as the College Level Examination Program (CLEP) program, the International Baccalaureate (IB) and the Advanced Placement (AP) program. Other programs include dual-credit enrollment, Tech Prep, Early College High Schools and actual attendance at the higher education institution while still in high school (Brand & Lerner, 2006; Karp & Hughes, 2008; Young, Joyner, & Slate, 2013).

Prior to the early 1970s, public secondary education leaders began experimenting with dual-credit enrollment programs aimed at increasing the educational output of the nation's high schools and their students, easing the transition between high school and higher education, and increasing levels of secondary education graduation, higher education participation, and higher education degree attainment (Fincher-Ford, 1997; Speroni, 2010). These programs offer concurrent enrollment in credit bearing, higher education courses at the community college level for high school students and allow students to accumulate meaningful numbers of higher education course credits, potentially sufficient to earn an Associate's Degree, prior to the completion of high school. For those students participating in these programs, time-to-completion and cost-to-completion of higher education terminal degrees may be decreased, offering the individual, household, and state significant fiscal and temporal savings (Smith, 2007). Not only have these programs evidenced important efficiencies in gaining human capital based levels of productivity, they have shown promising improvements in those underserved population least likely to enjoy the benefits of secondary and higher education participation and completion (Bailey & Karp, 2003; Swanson, 2008).

The very presence of dual-credit enrollment programs is important in and of itself as the strongest predictor of Bachelor's Degree completion is the intensity and quality of students' high school curriculum (Aldeman, 1999). Postsecondary success is predicated on an understanding of the expectations in college as well as rigorous academic course work in high school, suggesting that high schools and colleges should work together to ensure students' high school experiences are related to college expectations (, Aldeman, 1999; Venezia, Kirst, & Antonio, 2003). Dual enrollment programs are intended to do just that: They seek to blur the distinction between high school and college by allowing high school students to enroll in college courses and earn college credit while also fulfilling the high school credit requirements.

Initially, dual enrollment programs were targeted toward the most academically proficient high school students, with these programs being seen as a way to offer gifted students an academically challenging alternative to common high school programs (Rogers & Kimpson, 1992). Increasingly, educators and policymakers have required that a broader range of students benefit from these programs, including minority and middle and low achieving students who might not be prepared for college-level work in a higher education environment, but who have the capacity to perform when motivated and stretched. Many more students could achieve at the college level earlier if only they are challenged to do so, and by exposing high school students to the academic and social demands of college the need for remediation in college will be reduced (AASCU, 2002; Aldeman, 1999; Martinez & Bray, 2002; National Commission on the High School Senior Year, 2001).

Dual-credit enrollment programs have become an increasingly popular policy tool of state-driven, postsecondary reform, and are now available in all 50 states (Bragg, Kim, & Rubin, 2005), particularly where legislatures and state higher-education boards seek to increase access to higher education, and achieve greater collaboration and improved relationships between secondary and postsecondary institutions (Andrews, 2001; Andrews, 2004; Welsh et al., 2005,). This increased interest has led to a careful examination of the opportunities and challenges offered community-college educators and policymakers in almost every state during the 1990s. An examination of student records in the Kentucky Community and Technical College System analysis, consistent with those of Utah, New York, Texas, California, Tennessee, Illinois, Florida, Minnesota, Washington, Oregon and others reveals that more students are enrolling and succeeding in dual-credit courses. Participation rates of students from underserved populations are also increasing, indicating the efficacy of states' policies on dual credit to help institutions meet the state's reform goals for access and achievement in higher education. (Andrews, 2000; Andrews & Barnett, 2006;Boswell, 2001; Clark, 2001; Greenberg, 1989; Hoffman, 2003; Oregon Joint Boards of Education, 2000; Minnesota

Office of Higher Education; Porter, 2003; Syracuse University Project Advance 2004; Taylor, 2013; Taylor & Lichtenberg, 2013; Washington State Board for Community and Technical Colleges, 2002; Welsh et al., 2005).

By 2003, each of the 50 states allowed for some form of dual-credit enrollment. Of 40 states that had specified dual-credit enrollment policies or regulations, 17 included a mandate that dual enrollment opportunities be provided to students. While this may not require institutions in those states to develop and implement a dual enrollment program, it does suggest that high school students are required to have the opportunity to enroll in postsecondary education. In the remaining 23 states, specific legislation either gives high schools and colleges the option to provide dual enrollment opportunities to students, or state administered policies are such that state sponsored dual-credit enrollment programs are optional (Clark & Cambra, 2001; Karp et al., 2005; Martinez & Bray, 2002).

State admissions requirements for dual-credit enrollment programs vary widely, with some states requiring the passage of college placement exams, others requiring guidance counselor interviews and recommendations, others requiring particular demographic characteristics, and yet others only requiring the student to evidence a willingness to participate. States largely targeted higher achieving students in the earliest stage of dual-credit enrollment program evolution, and then transitioned to accepting students of all achievement levels, with particular targeting towards at risk or underserved populations. This is a reflection of the high rates of relative achievement obtained by underserved students participating in these programs (Bailey & Karp, 2003; Karp et al., 2005).

The growth of interest in dual credit programs provides considerable support for the idea that community college dual-credit programs can support the goals of educational reform, particularly those emphasizing increased participation in postsecondary education. The increase in the number of students enrolled, and the success of students in earning college credits while in high school, are evidence that students in high school are capable of meeting the increased expectations that dual-credit courses demand of them. As the scope of this study explores data from an entire state system, the results may encourage educators and policy makers to explore initiatives that blend the junior and senior years of high school with more intensive community-college experiences. Student records of the Kentucky Community and Technical College System reflect a national trend in respect to the growth of these programs and have enormous implications for the role and programming of community colleges in the United States (Andrews, 2001); by 2003, 8% of then current high school students across the country were participants in dual-enrollment programs (Kleiner & Lewis, 2005).

Instructor qualification and course content also varies. In 2003 only 13 states required specific criteria to be met in order for a high school instructor to teach a dual-credit course. Even those states that did not, however, were largely subject to requirements of the community college with which they were associated, such that in most cases the secondary education instructor teaching a dual-credit course evidenced certain qualification to do so beyond simply being authorized to teach at the high school level. In most cases these instructors' dual roles included being connected to the high school as full-time instructors and being associated with the community college as an adjunct instructor. Course content is regulated at the state level in 14 states as of 2003, such that the level of rigor is higher than a high school course of the same name. However, in those states in which state oversight is not explicit, course content in dual-credit courses, where measured, is found to be consistently higher than single–credit courses secondary education courses (Bailey & Karp, 2003; Johnson & Del Genio, 2001; Karp et al., 2005).

Dual-credit enrollment program financing needs add to the already overburdened secondary education fiscal situation. Where the program is administered from within the framework of a traditional high school, the added expense of dual-credit course offerings aren't likely to be offset with other program savings, such that the added expense must be borne by the student household, high school, participating community college, the state itself or some combination of these stake holders. As such, dual-credit enrollment program financing is a concern for states, with funding arrangements having implications for institutions and individuals. States have adopted varying requirements in respect to funding the higher education credit portion of these programs and in some cases institutions within a state having disparate policies (Hunt, 2007).

Some states require student households to pay all or part of the added expense, others place the burden on the participating institutions, and others provide state-level funding such that funding can be a strong incentive or disincentive for participation at all levels. Increasingly, student households have been required to bear the burden of the added expense, but this may not be as challenging as might be supposed in that the student household then may be relieved the cost of acquiring the student's accumulated higher education credits were they to have been obtained through more traditional higher education participation (Bailey & Karp, 2003; Bailey, Hughes, & Karp, 2003; Johnson & Del Genio, 2001; Karp et al., 2005; Martinez & Bray, 2002).

As many dual enrollment programs are free to participating students, the barriers to earning college credits are reduced and students have the potential to accumulate significant higher education credit hours, in many case up to 2 full years' worth, prior to entering college. This can shorten the time it takes to earn a degree and reduce significantly the overall cost of education (Orr, 2002). Given the financial advantages of such programs, advocates for their expansion have argued that confining them to only the most academically able limits access to educational opportunity and is thereby contrary to the mission of public education (Greenberg, 1988).

The Kentucky study specifically addresses and answers three questions: (1) Are more students enrolling and succeeding in dual-credit courses; (2) are more students from underrepresented populations enrolling and succeeding in dual-credit courses; and 3) what are the predictors of student participation and success in dual-credit courses? The resulting examination revealed significant increases in enrollment and growth in dual-credit courses, total credits earned by students, deficient credits, and cumulative college grade point average credits from fall 2000 to fall 2001, all indicating higher success rates for dual enrollment students. It further found statistically significant gains in enrollments over the two semesters by females, blacks, rural residents and students of low socio-economic status. In answer to the third question, the study found that analyzing all of the criterion variables in the study with the predictor variable was statistically significant; indicating that 15% of the variance in the student achievement in dual-credit enrollment courses were explained by the predictor set.[22] Together, the results presented warrant two conclusions: 1) Student performance in high school is most important in the explanation of student enrollment and success in dual-credit courses; and 2) the demographic characteristics of students also play an important role in the level of student participation and performance in dual-credit courses in community colleges.

Of those metrics commonly considered in respect to increased college readiness, participation in a dual-enrollment program was a stronger determinant of a high school students' higher education participation than were either grades or parents' education levels, otherwise considered to be among the strongest determinants of student performance and higher education participation (Smith, 2007). Further, exposure to a dual-enrollment program contributed to a student's higher educational aspirations and held a statistically significant and positive effect on higher education participation and degree attainment.

[22] Welsh et al. (2005) employed ANOVA estimations with criterion variables including total credits earned, deficient credits, cumulative GPA, ACT English and ACT Math; predictor variables include gender, ethnic group, residence and income.

Modern primary and secondary education systems no longer prepare students for entry into high-skills-demanding labor markets, but neither have they evidenced an ability to prepare students well for successful transition into and through higher education. Although many students would like to pursue a higher education degree, relatively few do so successfully. Less than one-fifth of ninth graders finish high school within 4 years, go on to college, and then complete a bachelor's degree within 6 years, with students of color and those who are economically representing yet more discouraging results, leading to the assertion offered by Kirst and Venezia that "Our education system is letting too many young people fall through the cracks" (Kirst & Venezia, 2006, p. 1).

Education reforms that focus on K-12 or higher education separately may not provide solutions to the underlying problem. The barriers perpetuating low levels of student success may also lie in the transition between secondary and postsecondary education. As such, many have begun to call for K-16 reform in an effort to bring together the two sometimes disparate educational structures. Effective state efforts to improve linkages between schools and colleges must extend well beyond local or regional collaborations. The educational needs of students in a domestic labor market requiring increasingly higher mean skills levels demands changes in fundamental policies that created and now reinforce the chasm between K-12 and postsecondary education (Haycock, 1996; Kirst & Venezia, 2006; Venezia et al., 2005).

Dual-credit enrollment programs effectively aid in easing the transition between these two education systems and may offer the conduit necessary to fill a 3 million worker gap between skills demanded and skills supplied referenced by Carnevale, Smith and Strohl (2010). Though community colleges, the most common higher education partner in dual-credit enrollment programs, aren't uniquely structured as technical institutions. However, their curriculum is more likely to provide for a smoother transition from secondary education to a technically oriented higher education experience, such that in some states the community college system is organized under the state's Community and Technical College banner. One such example is Georgia, where secondary to postsecondary education transitions through dual-credit enrollment has become particularly successful. A Harnish and Lynch (2005) study found that participation in dual-credit enrollment programs increased postsecondary technical college participation by 10% and attributed exposure to college while still in high school, increased offerings of courses made available through dual enrollment, and narrowing down of career choices through technical college course involvement as the most impactful contributors towards the students' successful postsecondary transition (Harnish & Lynch, 2005).

Young, Joyner and Slate (2013) found that dual-credit enrollment students' postsecondary, higher education exceeded that of non-dual-credit students generally, but particularly for those students whose secondary education performance was substandard prior to program enrollment. Specifically, they observed that students who completed dual credit courses enjoyed statistically significantly higher GPAs than did non-dual-credit enrollees; both male and female students who completed dual credit classes prior to college had statistically significantly higher GPAs than did gender-specific counterparts; and both Black and White students who completed dual credit classes prior to college had statistically significantly higher GPAs than did their race-specific counterparts - Asian students did not show a statistically significant difference in performance (Young, Joyner, & Slate, 2013).

## Early College High School as Secondary and Postsecondary Education Reform

In 2002 the Bill and Melinda Gates Foundation[23] provided funding to assist in facilitating the formation of the Early College High School Initiative and to expand on dual-credit enrollment programs and the Middle College concept – a particular form of dual-credit enrollment - first articulated by Janet Lieberman in 1972. Although the two reforms are not the same, the design of Early College High School is based on Lieberman's experience with Middle College, which experience resulted in a detailed list of requisites for success in the new initiative (Appendix A; Hoffman, 2003; Lieberman, 2004).

Early College High Schools are public schools accessible to students without respect to academic, demographic or financial condition and subject are to the funding, accreditation, and curriculum requirements of any public high school (Edmunds, Bernstein, Glennie, Willse, Ashavsky, Unlu, Bartz, Silberman, Seales and Dallas, 2010; Ongaga, 2010), but which have opted to accept students with a particular academic focus and immerse them in a college program absent many of the discretionary,

[23] The Bill and Melinda Gates Foundation; http://www.gatesfoundation.org/

expensive, and sometimes distracting programs of traditional high schools. Within the same budgetary and temporal constraints of a traditional high school, Early College High Schools provide secondary and higher education output simultaneously, saving the state and participants increasingly scarce fiscal resources and resulting in significant economic benefit to the state, households and graduates (Berger et al., 2010). However, to date this advantage has been more anecdotal than rigorously empiric. Early College High School is a hybrid, an innovation in secondary education in which the high school is located on or near a college campus and through which students are given the opportunity to complete their secondary education requirements concurrent with those of earning a postsecondary Associate's Degree. Where the Middle College concept covers the academic years of grades 9-12 and seeks to ease the transition between secondary and postsecondary education for underserved populations, the Early College High School takes this concept further by restricting participants to grades 10-12, while focusing on a particular course of study such as science, technology, engineering and math, and designing a curriculum intended to graduate students with both a high school diploma and higher education Associate's Degree.

Lieberman's Middle College structure features educational reforms contributing significantly to its success with students who have records of academic failure and multiple social problems and the Early College High School program continues this pattern. The results, based on data from New York City covering 1990-2000, were sufficiently impressive to motivate additional support and expansion, both to other Middle High Schools and the Early College High School model. Within the parameters of this study, 97% of the students stayed in school, compared to an approximately 70% rate of retention in the city as a whole; 87% graduated; 90% of the graduates went on to college; 11 major foundations contributed to the school and the program won 28 awards for excellence (Lieberman, 2004). Through the Middle College National Consortium,[24] the model has been replicated in sites across the country with similar results. The data from those settings in different states evidence that the structural changes succeed in a variety of locations and under different legislative parameters.

As Middle College students succeeded, Lieberman recognized that some of the 11th and 12th grade students had completed their secondary school requirements in less than the ordinary 4-year framework and were ready, academically and emotionally, to take college courses. Statistics for the 1999-2000 academic year reveal 4,581 Middle College students nationwide, of which 41% enrolled in more than 3,984 college classes, with a 97% pass rate, higher than that of the regular college freshman cohort.

In 2000, Middle College leaders received a Ford Foundation grant to pilot an enhanced curriculum design and structure to include features of the original Middle College (Appendix A) and add innovations based on student experience. The new model, Early College High School, incorporated some of the features of the previous design but emphasized different goals and required adherence to a strict parametric set,

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[24] The Middle College Consortium; http://www.mcnc.us/. The Middle College National Consortium believes that authentic school reform grows out of sustained collaboration among master practitioners, structured communication, and support for perpetual growth of leadership skills for all constituents. Centered on six Design Principles, MCNC schools bridge the high school and college experience for underserved youth leading to increased access to and success in college. A school-based, data driven practitioner network, Middle College National Consortium has successfully pioneered innovation in programs that serve districts, community colleges, universities, both public and charter, around the country for over 3 decades.

more intensive collaboration between secondary and higher education, and a more precisely articulated and accelerated academic trajectory. Lieberman noted that the success of Early College High School depends on destroying the hierarchy between secondary and higher education and building an equal partnership: “Realistically, the overriding consideration and incentives for Early College High School are the tangible financial savings in both real and social capital” (Lieberman, 2004, p. 4).

Based on a national study of students enrolled in grades 9-12 for years 2005-2011 funded by American Institutes for Research[25] (Berger et al., 2013), Early College High School students were significantly more likely to graduate from high school than their traditional high school counterparts. Though both groups have relatively high rates of completion, 86% of Early College High School participants graduate from high school compared to 81% of traditional high school students. Likewise, Early College High School students were found to be more likely to enroll in college following high school graduation with an enrollment rate of 80%. This is higher than students in other dual-credit enrollment programs as well as traditional high school students, with an enrollment rate of 71%. Though this gap decreases over time, comparison students’ enrollment rates did not catch up to those participating in Early College High School during the study period (Andrews, 2001; Berger et al., 2013; Waits, Setzer, & Lewis, 2005).

[25] American Institutes for Research (AIR), founded in 1946 as a not-for-profit organization, is one of the world's largest behavioral and social science research and evaluation organizations. Its overriding goal is to use the best science available to bring the most effective ideas and approaches to enhancing everyday life. The organization seeks to conduct its work with strict independence, objectivity and nonpartisanship.

In respect to higher education attainment, Early College High School participants are significantly more likely to earn a degree than comparison students. During the study period, 20% of Early College High School participants earned an Associate's or Bachelor's Degree, compared with only 2% of comparison students. The scenario in which Early College High School students find themselves and the length of the study exaggerate this finding somewhat as most Early College High School students are enrolled in higher education courses while in high school and in some state programs as many as 67% of these students graduate from high school coincident with being awarded an Associate's Degree; few dual-credit enrollees in traditional high schools enjoy this advantage (Berger et al., 2013).

Early College High School programs, originally envisioned to benefit underrepresented populations, did not offer a statistically significant impact on students based on subgroups. When controlling for gender, race/ethnicity, family income, first-generation college-going status, or pre-high school achievement Early College High School participants differed little, one subgroup from another, in high school graduation and higher education enrollment. However, in respect to degree attainment, female, minority, and lower income students showed increased rates of attainment and shorter time-to-completion than their Early College High School peers (Berger et al., 2013). Given current median levels for state spending on primary, secondary and higher education, closing the gaps would not only reduce the cost of high school and college for low-income students, but would also decrease the cost of higher education outcomes by $1,452 per Associate's Degree, and $3,607 per Bachelor's Degree. The high school diploma component of this alone suggests a state and federal level savings of $123,390,000 for the 90,000 students reported to participate in Early College High School programs in 2012, and another $74,247,200 in savings for the 56% of those participants who go on to earn an Associate's Degree (Vargas, 2013).

National organizations with sufficient funding to follow dual-credit enrollment and Early College High School program performance have been important to the expansion of these programs. The Middle College National Consortium, Jobs for the Future,[26] Early College High School Initiative, National Center for Education and the Economy,[27] National Center for Education Statistics, and National Alliance of Concurrent Enrollment partnerships[28] have each contributed heavily to the accumulated body of knowledge in respect to these important reforms in secondary to postsecondary education transitions. In cooperation with Jobs for the Future, Denver based Augenblick, Palaich and Associates, Inc. (APA) formulated a cost-to-completion model that provides a tool for quantifying the benefits of making the progress of students more efficient through high school and into and through college. The model is capable

[26] *Jobs for the Future* (www.jff.org) is a Washington, DC based research organization that works with industry partners to design and drive the adoption of education and career pathways leading from college readiness to career advancement for those struggling to succeed in today's economy.

[27] National Center for Education and the Economy (http://www.ncee.org/). Since 1988, NCEE has been researching the world's best performing education systems to unlock their secrets. We focus on their standards, instructional systems and assessment designs. We look at the way they govern, finance and organize their systems. We use this information to provide groundbreaking designs for high performance education systems at the national, state and local levels. For much better student performance. For all of our students.

[28] National Alliance of Concurrent Enrollment Partnerships; http://www.nacep.org/about-nacep/mission-history/. The National Alliance of Concurrent Enrollment Partnerships (NACEP) works to ensure that college courses offered by high school teachers are as rigorous as courses offered on the sponsoring college campus.

of quantifying the impact of improving progress for populations by income status (Palaich, Augenblick, Foster, Anderson and Rose, 2006) . With this type of calculation, it's possible to reveal the benefits relative to the costs, particularly great for strategies that target low-income students and raise their rates of degree completion (Vargas, 2013, p. 1). Participation in Early College High School and other dual enrollment programs increase the likelihood of completing a higher education degree within 6 years of high school graduation by 1.65 times. For those students who earn at least 20 college credits while in high school the experience results in a reduction of $4,711 for an Associate's Degree and $4,194 for a Bachelor's Degree (Vargas, 2013, p 10).

Palaich et al. (2006) notes in its preface that states such as California and New York, in which very different though economically challenged education finance systems are found, the states might expect to yield $1.44 to $2.11 for every dollar invested in Early College High Schools than in traditional high schools over the course of 15 years, and $2.51 to $3.95 over the course of 25 years; this in addition to the returns accruing to the individual from higher skills preparation and shortened time-to-completion of higher education degrees. Palaich's report further notes that students and families participating in Early College High Schools "benefit tremendously" compared to the benefits accruing to those participating in traditional high school careers (Palaich et al., 2006, Executive Summary). The APA Model for return on investment makes the case for students and families benefiting from participation in Early College High Schools, demonstrating how Early College High School generates more benefits for their students and a greater return on investment than comparable traditional high schools, and documents the benefits states may receive from investing in cost-effective Early College High School sites and programs.

Based on Palaich's estimates of select California, Texas and Ohio Early College High School participant expenses and projected earnings over 15- and 25-year time frames, individual level returns on Early College High School participation exceed their traditional high school counterparts by 1,511% for those graduates who attend some college, 1,197% for those earning an Associate's Degree, and 1,088% for those earning a Bachelor's Degree. The inverse relationship between increased rates of return and degree attainment are the result of the low or no-cost nature of Early College High School (Palaich et al., pp. 18-2020, Tables 2 and 3). The benefits of the Early College High School model include reduced drop-out rates for underserved populations, increased student persistence and graduation rates, and increased levels of earning college credits and terminal degrees. The cost variations depend on the arrangement the school has with its higher education partner, but is minimal in the APA study; as are the costs borne by student households.

National Education Longitudinal Study (NELS) based estimates tend to present a more positive picture of the percentage of Early College High School students completing degrees than do state estimates. The NELS data support improved higher education degree completion in each category across the general and underserved student populations. However, similar state estimates present higher Associate's Degree completion than does the NELS and a lower percentage of both traditional high school and Early College High School students completing some college: 29% versus 7%

of Early College High School participants NELS versus state estimates, and 26% versus 10% of traditional high school participants. Bachelor's Degree completion in the NELS and state estimates were the same at 28% for Early College High School participants, but 10% versus 28% for traditional high school participants (Swanson, 2008).

Dual enrollment has the potential to alter the relationship between high school and college. At one extreme, it could fundamentally change the content of the high school years and promote a more focused and perhaps coherent role for postsecondary institutions, particularly community colleges. At the other extreme, it could reduce the amount of effective education received by students if they complete high school with college credits, having learned exactly what they would have in a regular high school program (Bailey, Hughes, & Karp, 2003).

In virtually all states, dual-credit enrollment programs are found in both traditional public high schools and in charter high schools. Charter schools are a particular public education innovation in and of themselves, and while not the focus of this study, there is an important overlap. Some states, including Utah, utilize the charter high school structure exclusively for Early College High School program development. Several criticisms often leveled at Early College High Schools and charter schools in general include cream skimming, demographic bias, and added expense. "Cream skimming" suggests that these schools recruit and accept only the best of students for their programs,[29] though there is little objective evidence to support such

[29] Cream skimming suggests that these schools recruit and accept only the best of students for their programs.

claims, they remain the foundation of bias many educators and policy makers cling to when considering these types of programs.

## Dual-Credit Enrollment and Early College High School Programs in Utah

Though high by national standards, the 2013 graduation cohort of Utah public high school students included only 81% of those expected (Utah State Office of Education Yearbook, 2013), a figure which, though climbing since 2000, had been relatively constant for too long (Heckman & LaFontaine, 2010). State-level data in respect to income and minority status reflects Utah's minority population performing poorly compared to national figures with the greatest differentials represented for Hispanic and Asian students (Figure 2.1),[30] Utah's most rapidly growing student populations (Alliance for Education, 2011). In 2009 more than 10,500 Utah high school students failed to graduate with their peers, representing lost lifetime earnings of more than $2.7 billion (Alliance for Education, 2011).

With respect to the state of Utah, the following figures aid in illustrating the potential economic benefits to households and the state of investing in an improved high school system that better prepares all high school students for graduation (Alliance for Excellent Education, 2009). Were Utah to increase graduation rates to 100%, admittedly an optimistic target, the state might realize the following economic benefits:

[30] Utah State Office of Education Cohort Graduation and Dropout Rate Reports, 2012 and 2013.

- $79.2 million in lower health care costs over the course of the lifetimes of each class of dropouts.
- $327 million increase in accumulated wealth if all heads of households had graduated from high school.
- $780 million added to Utah's economy by 2020 if minority students graduated at the same rate as their nonminority counterparts.
- $17.7 million savings in annual community college remediation costs and lost earnings if Utah's high schools graduated all students ready for college as part of $52 million savings in overall higher education remediation costs and lost earnings (Alliance for Excellent Education, 2011).
- $39.3 million in reduced crime spending and increased earnings each year if the male high school graduation rate increased by just 5%.

In an effort to improve the level of worker productivity and incomes generally, and to specifically thwart the problem represented by the growing gap between skills demanded of US workers by the evolving global market place and skills developed through the existing public education infrastructure, states have begun to adopt various initiatives focused on improving outcomes generally and better preparing their respective workforces. Utah's effort includes a variety of innovative programs intended to improve high school and higher education outcomes in support of improved levels of worker productivity including the Utah System of Higher Education's "15 to Finish" and a public/private initiative titled *Prosperity 2020.* [31] Each of these initiatives is complemented by a more rigorous high school education such as that provided through Dual-Credit Enrollment and Early College High School programs.

The “15 to Finish” initiative[32] seeks to reduce the average number of years to complete a Bachelor’s Degree from a commonly experienced 5 to 6 years down to 4 years, which reduction not only improves higher education affordability and completion rates, but prepares the student to enter the job market 1 to 2 years earlier. Those students who accumulated college credits while in high school are more likely to succeed with type of time-frame owing not only to the accumulated credits, but to the lower need for remedial education while in college resulting from the more rigorous course taken while in high school.

Utah business, legislative and education leaders came together to form *Prosperity 2020,* a Utah public/private partnership seeking to mobilize business, education, and community partners to improve educational achievement and workforce literacy, and increase access to service opportunities. Among the goals of this partnership is for 66% of Utah working adults to hold postsecondary certificates or degrees, up from 43% in 2013. Another of the group’s top three goals is for Utah to become a “Top Ten” STEM center for technology and business jobs, whereas Utah ranks 11th in the nation for technology jobs as a share of total employment, but 36th among

[31] Prosperity 2020, http://prosperity2020.com/

[32] The “15 to Finish” campaign encourages Utah’s college students graduate on time and save tuition. Most degrees in the Utah System of Higher Education require at least 120 credits to complete, so if students want to finish their associate degree in two years or bachelor’s degree in four years, they need to take a minimum of 15 credit hours each semester. http://higheredutah.org/preparepay/15tofinish/ and http://15tofinishutah.com/#resources

states for technology jobs and businesses combined. The group's plan includes making strategic investments in Utah primary and secondary public education of $43.6 million and $20 million in public higher education.

Though not directly a result of *Prosperity 2020's* goals, Utah's support for Early College High School and Dual –Credit programs has aided in the state's progress towards the partnership's goals. The state's six Early College High Schools [Academy for Math, Engineering and Science (AMES); Intech Collegiate High School; Itineris Early College High School; Northern Utah Academy for Math, Engineering and Science (NUAMES); Success Academy; and Utah County Academy of Sciences (UCAS)] each support STEM or STEM related curriculum. In 2012 Utah's Early College High Schools graduated 781 students out of 41,496 high school graduates throughout the state, less than 2%. In addition to the scholarship funds earned, Utah's Early College High School students who receive their Associate's Degree within 3 months of high school graduation are eligible to receive the state's New Century Scholarship[33] providing an additional $1,100 per semester for each of 2 years of higher education costs at any school, public or private, within the state. These schools enjoyed a dropout rate of less than 2% compared to a state dropout rate of 12% for the year, and a dropout rate of over 7% for the state's other dual-credit enrollment students.

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[33] The New Century Scholarship encourages Utah high school students to accelerate their education by earning an Associate's Degree in high school from an institution within the Utah System of Higher Education. The scholarship may be used at any 4-year public college or university in the Utah System of Higher Education, as well as at Brigham Young University-Provo, LDS Business College, and Westminster College. The New Century Scholarship is modified each year as a result of legislation. http://higheredutah.org/scholarship_infonew-century-scholarship/

Dual-credit enrollment programs in Utah are required to follow guidelines established by the Utah State Legislature, inclusive of the program's purpose, student eligibility, school and student participation, credit transfer, the program's fiscal attributes. Utah Administrative Rule R277-713 (UAR R277-713, 2014), effective July 1, 2014,[34] provides a comprehensive framework within which all Utah public high schools must operate with respect to dual-credit enrollment programs, specifically concurrent enrollment programs. As directed by the administrative rule and consistent with other dual-credit programs across the nation, Utah's express purpose for offering dual-credit courses is to "provide a challenging college-level and productive secondary school experience, particularly in the senior year, and to provide transition courses that can be applied to post- secondary education" (UAR R277-713, 2014, p. 2).

Like most states, Utah requires certain eligibility standards for dual-credit participation consistent with participation in the higher education institution offering the course. The rule states, "To ensure that a student is prepared for college level work, an appropriate assessment shall be administered to the student prior to participation in all concurrent mathematics and English courses, and to determine that the student meets prerequisites previously established for the same campus-based course by the sponsoring USHE institutions" (UAR R277-713, 2014, p. 3). Students interested in attending Utah's Early College High Schools must apply for a limited number of openings each year and acceptance is based on a process of interviews and passing of an entrance examination, the successful requirements for which are no different from those

[34] Previous Utah Administrative Rules directing Utah's dual-credit programs provided similar guidelines. UAR R277-713 updates those guidelines with limited functional differences.

required for advancing from one grade to another in the broader Utah secondary education environment. In the event that the number of applicants exceeds available openings, applicants are subjected to a lottery system randomly assigning openings to applicants. Finally, Utah's Early College High School students receive the same per pupil funding from state and federal sources as their traditional counterparts, require no individual or household contributions, and college tuition for the credit hours earned out of the school's allocated state and federal funds rendering them the least expensive of all higher education options for public education students in the state.

Further, Utah's dual-credit enrollment programs are intended to "allow students the option to complete high school graduation requirements and prepare students to meet college admission requirements at the conclusion of the eleventh grade…" (UAR R277-713, p. 3); participation is limited to students in the $10^{th}$ through $12^{th}$ grades. Eligible courses include English, mathematics, fine arts, humanities, science, social science, world languages, career technical programs, and technology intensive concurrent enrollment (TICE[35]) courses with the express purpose of assisting students towards a higher education degree.

The Utah System of Higher Education (USHE) is charged with the responsibility of ensuring the quality of content and delivery of these courses, with similar requirements

[35] Technology Intensive Concurrent Enrollment (TICE) is a collaborative program sponsored by the Utah System of Higher Education (USHE) and the Utah System of Education (USOE). TICE courses are "technology intensive," meaning they are designed as a hybrid blend of teaching and learning activities that take place in class and online. They are also "concurrent enrollment" so qualified high school juniors and seniors may enroll and earn credit in one of the institutions in the Utah System of High Education (USHE) as well as meet graduation requirements from their high school. http://www.uen.org/concurrent/

for content and instructor qualifications to those for a similar course being taught through the higher education institution responsible for the course. This results in classes being taught with the same texts and materials to high school students seeking dual-credit as those taught to traditional college students by instructors who, at a minimum, meet adjunct instructor qualifications for that institution. In practice, these courses are taught by high school teachers also engaged as adjunct instructors in Utah higher education,[36] giving rise to one of the common criticisms leveled at dual-credit courses by those outside of these systems, that the quality of instruction is of lesser quality than the student may otherwise receive had the course been taken while in a traditional college setting. Given the extensive use of graduate student instructors and the relatively high level of qualification held by most Utah high school instructors, these criticisms are interesting and anecdotal, but may be without foundation.

Similarly, critics of Utah dual-credit programs note a difference in the credit purported to be available students who take these courses compared to that which is accepted in traditional higher education institutions. However, Utah's administrative code is clear on this point as the rule states, "College level courses taught in the high school carry the same credit hour value as when taught on a college or university campus and apply toward college/university graduation on the same basis as courses taught at the USHE institution to which the credits are submitted" (UAR R277-713, 2014, p. 6). Students seeking to transfer higher education credits earned through Utah's dual-

[36] Adjunct instructors teaching concurrent enrollment courses to Utah's public high school students are employed by the higher education institution offering the course, but are not compensated by that institution. Their compensation is exclusive to the high school and school district with which they're contracted.

credit enrollment programs may well face issues with respect the quantity of credits accepted by the receiving institution, just as they have with other credits earned through the Utah System of Higher Education.

Funding for Utah's dual-credit courses is provided largely through funds allocated by the Utah State Office of Education through its annual district resource allocation memo.[37] This is provided based on student higher education credit hours earned and differs for concurrent enrollment and advance placement courses. For the 2014 academic year ending June 30th, Utah public education allocated less than $6.9 million for dual-credit enrollment out of more than $2.9 billion provided those public high schools offering such courses: A total of 0.24%. When broken down by type of high school the allocation memo shows that traditional high schools offering dual-credit courses were budgeted to receive 0.38% of their funds for the support of these students/courses, non-Early College High School charter high schools were allocated 0.21% and Early College High Schools were allocated 3.56% of their budget in support of dual-credit courses. The significant difference between Early College High Schools and others reflects the mission and purpose of these schools with respect to the number of higher education credit hours their students are designed to accumulate.

The burden placed on student households for dual-credit programs tends to differ based on where the course is being delivered and by whom it is taught. Where dual-credit courses are offered through the traditional high school or charter high

[37] Figures derived from Utah State Office of Education Allocation Memo, Minimum School Program Monthly Allotment for Fiscal Year 2014, Utah State Office of Education, pp. 1-352, April 21, 2014

school that is not an Early College High School, student households may be assessed fees as allowed by the Utah Administrative Rule. These fees are limited to $10 per credit hour for those courses taught at the high school by high school instructors also engaged as higher education adjunct instructors, $30 per credit hour for those courses taught at the sponsoring college by its instructors, and $15 per credit hour for those courses taught via video conferencing.

For those students enrolled in a traditional or non-early college charter high school policies regarding who pays the allowable fees differ by district with student households being required to pay much or all of the allowable fees. Courses required for high school graduation taken through one of Utah's six Early College High Schools tend to be provided without additional cost to the student household, the high school's budget bearing the expense. Some courses taken by Early College High School students are not concurrent enrollment or advanced placement courses and are outside of the course list provided by Utah's Administrative Rule. Those non-dual-credit enrollment college courses taken by Early College High School students, which also fulfil high school course requirements and are necessary for high school graduation, such as some science or other STEM courses, are paid for by the Early College High School out of its state sponsored revenues. Utah public education students consistently rank above the national average in mathematics and science at the $4^{th}$–, $8^{th}$- and $11^{th}$-grade levels (Hess, Kelly, & Meeks, 2011). As such, additional emphasis placed on STEM (science, technology, engineering, and mathematics) education among Utah students via dual-credit course programs stands to yield greater competitive gains than might be experienced in other states.

Where these courses are taken by Early College High School students for the purpose of earning sufficient additional higher education course credit to receive an Associate's Degree coincident with earning their high school diploma, the student household is often required to bear the higher education tuition expense as agreed upon by the Early College High School and the sponsoring college. Early College High School administrative staff personnel note that those students who earn sufficient credits to receive their Associate's Degree often pay upwards of $1,000 in higher education costs to order to do so. Compared with an average 2-year in-state tuition cost of $8,640[38] required by Utah's public colleges and universities for sufficient credit hours to earn an Associate's Degree, $1,000 is a modest expense. However, just as with most other forms of higher education, for those households unable to afford the additional higher education expenditure it may be financed by federal student loans or other student financial aid programs.

Dual-Credit Enrollment differs from Early College High School in Utah in that Dual-Credit Enrollment is motivated by a student's choice to enroll in a more challenging course, either a concurrent enrollment or advanced placement course, providing course credit for high school and college. In Utah's Early College High School program these dual-credit courses are included in a somewhat less flexible curriculum such that

[38] Annual tuition costs for full time students enrolled in one of the eight public colleges in the Utah System of Higher Education (USHE) average $4,320 for in-state students, with a range from $2,830 (Snow College) to $6,511 (University of Utah). College Tuition Comparison Summary Table offered by College Tuition Compare: http://www.collegetuitioncompare.com/compare/tables/?state=UT&type=Public

wherever possible, those high school courses required for high school graduation by the Utah State Office of Education are substituted with concurrent enrollment and advanced placement courses taught at the high school or associated college on behalf of the high school. Where Early College High School students choose to earn an Associate's Degree coincident with receiving their high school diplomas, several additional college level courses are required. Depending on the student's preferred course selection, these courses may be taken at the Early College High School as additional concurrent enrollment course, while others may be taken at the associated college. These program differences result in a significant difference in the number of higher education course credits earned by Dual-Credit Enrollees as compared to Early College High School enrollees.

Coincident with the introduction of dual-credit enrollment programs in Utah in the mid-1990s was the introduction of the state sponsored New Century Scholarship (NCS). Utah high school students completing an Associate of Arts degree through dual-credit enrollment are eligible to receive the scholarship which, at the time of its inception, allowed the student up to 5 years to complete the remaining years for a Bachelor's Degree and while so doing, the scholarship provided 75% of the remaining 2 years of tuition. To be awarded the student is required to complete the Associate's Degree requirements within 3 months of high school graduation with a cumulative GPA of no less than 3.0, minimum ACT score of 26, and must remain in Utah for their higher education degree attainment (Utah Code 53B-8-105[39]).

Though this may appear to be yet another in a long line of higher education expenses funded by the state, Utah's New Century Scholarship has been widely recognized to be self-sustaining as early graduation from college allows students to complete their higher education experience sooner and gain labor market entry at an earlier age, thus supporting the current tax base and making a positive contribution to society. In this manner, both the student and the state benefit from early graduation (Bracco & Martinez, 2005; Kearl, 2012; Kearl, Byrnes, & Maahs-Fladung, 2013).

Kearl, Byrnes and Maahs-Fladung (2013) examined the effects of receiving this scholarship and determined that the New Century Scholarship does expedite Bachelor degree completion for both males and females with an average time to completion of 3.57 years, fully 1.13 years less than the national average of 4.7 years to Bachelor degree completion for those already in possession of an Associate's Degree (Complete College America, 2012). Another important finding was the rate of completion for New Century Scholarship recipients with a Bachelor degree at 83.2%. For those dual-credit enrollment and Early College High School students who are eligible and qualify for the New Century Scholarship, it improves upon the already positive household financial effects of these programs by further decreasing the time-to-completion and cost-to-completion of the higher education experience.

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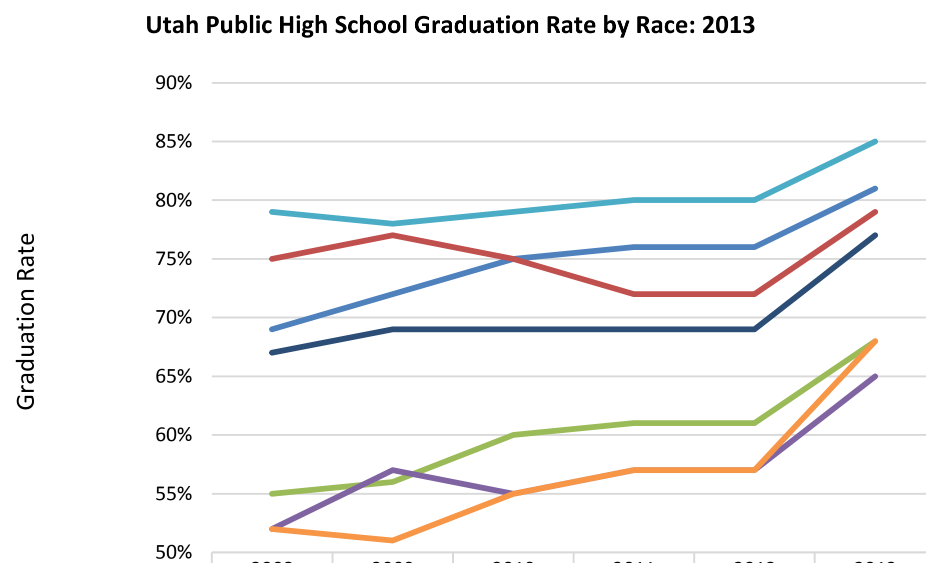
[39] Utah Code 53B-8-105. New Century scholarships - High school requirements: http://le.utah.gov/~code/TITLE53B/htm/53B08_010500.htm

Utah Governor Michael O. Leavitt's term in office (1993 –2003) reflected a commitment to improve educational innovation in support of increased productivities and outcomes for the state and the state's growing economy and population. Later, as Secretary of the U.S. Department of Health and Human Services, Leavitt pursued his education innovation agenda at the national level while subsequent Utah governors extended Utah's participation in the nation's growing dual-credit enrollment movement and further into the emerging Early College High School initiative. In 2015 Utah will graduate its 10th cohort of public high school students having completed high school coincident with being awarded a 2-year higher education degree through the state's Early College High School program.




| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|
| All Students | 69% | 72% | 75% | 76% | 76% | 81% |
| Asian | 75% | 77% | 75% | 72% | 72% | 79% |
| Black | 55% | 56% | 60% | 61% | 61% | 68% |
| American Indian | 52% | 57% | 55% | 57% | 57% | 65% |
| White | 79% | 78% | 79% | 80% | 80% | 85% |
| Hispanic/Latino | 52% | 51% | 55% | 57% | 57% | 68% |
| Pacific Islander | 67% | 69% | 69% | 69% | 69% | 77% |

**Figure 2.1 Utah Public High School Graduation Rate by Race: 2013**

# 3. METHODOLOGY

This chapter outlines the major research questions of this study with their outcomes, research design and the analytical approaches taken. Detailed discussions of the foundations statistical methods used in estimating the study's outcomes, Propensity Score Matching as a quasiexperimental design method and Receiver Operating Characteristics Analysis are also included.

## Research Questions

The general question addressed in this study is, "What are the effects of student participation in Utah's public education career paths?" Specifically, the experience of the 2008 and 2009 Utah public high school graduation are examined separable by their self-selection into three career paths: Traditional, Dual-Credit Enrollment, and Early College High School, wherein Dual-Credit Enrollment and Early College High School are considered treatments on the selecting student populations and Traditional students are a generalized control group. This leads to a consideration of the primary claim of Dual-Credit Enrollment and Early College High School programs: Dual-credit enrollment programs improve high school and higher education participation and performance for program participants generally, and underrepresented students specifically. In consideration of the effect of these treatments, or paths, on the general student populations, an examination into outcomes for high school graduation and performance, higher education enrollment and graduation, and higher education graduation, time-to-completion and degree attainment is offered (Appendix D). These same treatments and outcomes are then separately considered for underrepresented students with respect to gender, race, income and English language learner status (Appendix E through M).

## Expected Outcomes

Dual-Credit Enrollment and Early College High School programs have been observed to provide meaningful benefits in respect to the targeted outcomes in national studies (An, 2009; Karp et al., 2007; Kim & Bragg, 2008; Speroni, 2011; Struhl & Vargas, 2012; Swanson, 2008; Taylor, 2013) and we would expect to find their application in Utah public education to offer similar results. We may expect to find improvement in high school graduation experience, postsecondary higher education enrollment, and higher education degree attainment for those students who have accumulated higher education credits prior to high school graduation and a decrease in the number of days between high school graduation and Bachelor's Degree attainment, reflective of the "head start" these students have on their peers in the untreated group.

Interestingly, what we find is that the estimated outcomes on secondary education standardized testing is nominal, while the effect on high school graduation, and postsecondary higher education enrollment is substantial, as are the effects on higher education graduation and degree attainment. Finally, we observe meaningful reductions (improvements) in higher education time-to-completion at the Associate's

Degree level, though such reductions remain present at lesser levels at the Bachelor's Degree levels. These effects are observed for both the general and underrepresented student populations, and as expected, are greater for underrepresented students.

While some expect these improved outcomes may be the result of those influences attributing to the students' participation in the selected treatments rather than the result of the treatments themselves, this study seeks to examine the treatments and their relation to the outcomes. As such, the adoption of a quasiexperimental estimation design intended yield credible causal inference, Propensity Score Matching, is employed (Abadie & Imbens, 2012; Dehejia & Wahba, 2002; Peikes, Moreno, & Orzol, 2012; Rosenbaum & Rubin, 1983). Propensity Score Matching is used extensively in modern, nonexperimental social science and education research and has become widely accepted as a method in support of credible causal inference. However, it bears noting that Propensity Score Matching has its limitations, and while causality credibility may be inferred, the inference is only as strong as the instruments employed in the matching process (Austin, 2011; Caliendo & Kopeinig, 2005; Rosenbaum & Rubin, 1983).

Further, Receiver Operating Characteristics Analysis (ROC Analysis) is employed to identify optimal Propensity Score Matching models for each of the major outcomes given the available variables and data. First developed to aid radar operators in accurately interpreting radar imagery in World War II, ROC Analysis has been widely used to assist in visualizing and analyzing the behavior and accuracy of diagnostic systems with various healthcare applications since the 1970s (Eng, 2005) and has more recently been applied in evaluating and comparing a wider range of algorithmic metrics employed in social sciences research, machine learning evaluations and other interpretive analytical processes (Fawcett, 2006).

## Estimation Methodology

To estimate the effects of Dual-Credit Enrollment and Early College High School, this study employs a probit form of Propensity Score Matching as an alternative to standard linear regression estimation forms such as OLS and GLS in support of assessing causal inference (Abadie & Imbens, 2012; Dehejia & Wahba, 2002; Peikes, Moreno & Orzol, 2012; Rosenbaum & Rubin 1983,). Propensity Score Matching has been used extensively in recent decades to provide causal inference in education studies, including those related to Dual Credit Enrollment and Early College High School (An, 2009; Speroni, 2011; Struhl & Vargas, 2012; Taylor, 2013). The method provides a quasiexperimental design structure for nonexperimental studies in which a prescribed treatment is applied to a portion of the study participants via self-selection (nonrandomized participation) resulting in endogeneity or self-selection bias.

Matching occurs through the selection of available pretreatment independent variables, such that matched pairs are observable, distinguishable by their treatment selection or avoidance. The average treatment effects (ATE) are measured for the sample population and are then compared to the average treatment effect on the treated (ATET). “When relevant differences between any two units are captured in the observable (pretreatment) covariates, which occurs when outcomes are independent of assignment to treatments conditional on pretreatment covariates, matching methods can yield an unbiased estimate of the treatment" effect (Dehejia & Wahba, 2002, p. 151).

Social science research suffers from at least two fundamental difficulties: 1) To apply potentially injurious experimental treatments, with long-lasting effects, is considered immoral by some and irresponsible by most, as once applied to a portion of the population the effects of treatment cannot reasonably be undone, and 2) where treatments are applied via self-selection, or in a nonexperimental manner, there is no reasonable way to discern what outcomes may have occurred had the treatment not been applied: the counterfactual.

From a theoretical standpoint, the way to obtain a counterfactual is to use the same participants under both treatment and control conditions, restoring internal and external conditions to initial values present before participants encountered either. As such, participant outcomes are observed under the treatment (factual) and the control condition (counterfactual), and the difference in outcomes is the individual treatment effect. Averaging individual treatment effects for both groups and then subtracting those average from the quantified outcome (observed or estimated) yields the average treatment effect (Murnane & Willett, 2011, p. 33-34).

However, resetting internal and external conditions isn't feasible in social science research and as such, it is virtually impossible to obtain the outcome value of the control condition for individuals in the treatment group, and it similarly lacks feasibility to obtain the outcome value of the treatment for individuals in the control group. Since observing or identifying counterfactual data isn't feasible in social science research there will always be missing data when calculating the average treatment effects (Holland, 1986; Murnane & Willett, 2011; Shadish, Cook, & Campbell, 2002).

The average treatment effect is represented by the equation

$$E(\delta) = E\ (Y^1 - \ Y^0) \tag{3.1}$$

where δ represents the difference, $Y^1$ is the average outcome for the treatment group and $Y^0$ is the average outcome for the control group (Morgan & Winship, 2007; Murnane & Willett, 2011). In this structure *D* indicates an individual's assignment to the treatment (*D = 1*) or control condition (*D = 0*) and separately observe outcomes where *D = 1* and where *D = 0;* to estimate the counterfactual, however, we would need to observe when *D = 0 and D = 1* for the same participant. As observation of the counterfactual is infeasible (Holland, 1986; Morgan & Winship, 2007; Murnane & Willett, 2011), we estimate the average outcomes of the control group to determine the average treatment effect.

The average treatment effect is simply one of three potentially estimated conditional average treatment effects; the others are the average treatment effect on the control (ATEC) and the average treatment effect on the treated (ATET). It is the average treatment effect on the treated (ATET) that is of interest in this particular study. The average treatment effect on the treated is the effect on those participating in the treatment and is defined as

$$E\ (Y^1 - \ Y^0) \mid D = 1 \tag{3.2}$$

where the average treatment effect on the treated (ATET) can be thought of in this study as the average effect of either Dual-Credit Enrollment or Early College High School on the outcomes of those students participating in either of these programs in comparison to those students who have not opted for participation, but for whom program access is readily available. In this study we separate Dual-Credit Enrollment and Early College High School treatment effects using the labels *DCE Only* and *ECHS Only*, but also consider the effects of general participation in dual-credit enrollment using the label *DCE General*. In the case of *DCE Only*, the control group is those students who did not participate in any form of dual credit enrollment, and the control group for considering of *ECHS Only* is also those who did not participate in any form of dual-credit enrollment.

Note the differentiation of the terms *Dual-Credit Enrollment* and *dual-credit enrollment*. *Dual-Credit Enrollment* is used to denote those students who participated in dual-credit courses providing both secondary and higher education course credit while enrolled in a traditional public high school. This is differentiated from *dual-credit enrollment*, which simply denotes those students who participated in any type of dual-credit course programs, either *Dual-Credit Enrollment* or *Early College High School*, while enrolled in public high school.

As causal inferences cannot be determined based on a counterfactual, alternative methods must be used for making causal claims. The theoretical basis for drawing causal inference in social science research is established by John Stuart Mill in his proposition that there are three conditions for claiming a causal relationship: a) The cause and effect must co-vary; b) the cause must precede the effect; and c) alternative explanations must be excluded (Shadish, Campbell, & Cook, 2002). The latter of these three conditions is the most challenging to meet as “the researcher must be able to discount all other plausible explanations — other than the anticipated causal explanation — as the link observed between the hypothetical cause and effect” (Willett & Murnane, 2011, p. 29). In experimental study designs in which participants are randomly assigned to treatment and control conditions, this more challenging condition may be met as all participants have equal opportunity to be assigned to the treatment and control conditions, while in nonrandom studies self-selection into an available treatment yields biased and confounding results.

Randomization causes the treatment variable ($X$) to be independent of a potential outcome ($Y$). This assumption is the *strongly ignorable treatment assignment* and a central assumption of experimental design. However, as noted, social science research does not reasonably allow for experimentation. In the sort of nonexperimental, or observational data, used in this study, we have no control over treatment and control assignment, and as such participants self-select into treatment or control conditions.

### *Propensity Score Matching as a Quasiexperimental Design*

Given that most social science research is inconsistent with experimental study, quasiexperimental design is employed to suggest causal inference. Quasiexperimental design seeks to describe Mills’ exclusion of alternative explanations condition such that “the logic of causal inference in quasi-experimentation requires careful and detailed attention to identifying and reducing the plausibility of alternative causal explanations” (Shadish, Campbell, & Cook, 2002, p. 105). The use of matching based on a set of pretreatment variables seeks to fulfill this condition, but does so with a noted level of imperfection. With that said, it remains the strongest analytical method available given the variables and data at hand.

Matching is a quasiexperimental design used when only posttreatment outcomes are available and when endogeneity or self-selection bias is an issue, as in this study. When there is no pretreatment observation on the measured outcomes, matching methodologies have become commonly employed to reduce bias through the formation of treatment and control groups and via matching based on pretreatment variables independent of the posttreatment outcomes. Endogeneity bias occurs as self-selection into a treatment or control group results in differences in unit characteristics between conditions not independent of outcome differences (Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1983; Shadish, Cook, & Campbell, 2002), resulting in systematic differences among participants in the treatment and control condition that may influence the outcome.

### ***Propensity Score Estimation***

Propensity Score Matching is the process whereby we may group participants with similar propensity scores based on matching variables, such that treatment and control groups each contain participants with statistically identical characteristics. The use of multiple matching variables, inclusive of small gradient measurements in a subclassification method, is a frequently cited method in education research (Cochran, 1968; Shadish, Cook & Campbell, 2002). However, endogeneity or self-selection bias may not be completely eliminated when using matching as unobserved variables cannot be matched and there may be remaining hidden bias (Shadish, Cook,, & Campbell 2002, Caliendo & Koepeinig 2005).

In this particular study we match participants in the selected high school graduation cohorts based on demographic variables (race, gender, income and English language learner status) as well as pretreatment, standardized test performance (CRT scores for Pre-Algebra, 8th-Grade Language Arts, and 8th-Grade Science). By so doing, we're able to observe the average treatment effect on the treated (ATET) in the subject population defined as

$$\tau_{ATET} = E(\tau|D = 1) = E[Y(1)|D = 1] - E[Y(0)|D = 1]. \qquad (3.3)$$

Since the counterfactual $(E[Y(0)|D = 1])$ cannot be observed for the treated population we substitute the mean outcome for the untreated student population $(E[Y(0)|D = 0])$ into the ATET equation such that

$$E[Y(0)|D = 1] - E[Y(0)|D = 1] = \tau_{ATET} + E[Y(0)|D = 1] - E[Y(1)|D = 1] \quad (3.4)$$

The difference between the left hand side of the equation and $\tau_{ATET}$ is the self selection bias and the true parameter $\tau_{ATET}$ is only identified if

$$E[Y(0)|D = 1] - E[Y(1)|D = 1] = 0. \qquad (3.5)$$

Propensity Score Matching methodology introduces the propensity score to match variables as a method to obtain the average treatment effect using observational data (Rosenbaum & Rubin, 1983, 1984, 1985). The propensity score ($E_i$) represents the probability of selection into the identified treatment and was defined by Rosenbaum and Rubin (1983) to be the probability of treatment assignment conditional on observed baseline (pretreatment) covariates:

$$E_i = \rho\ (Z_i = 1|X_i). \tag{3.6}$$

Caliendo and Kopeninig 2005 further define the propensity score matching (PSM) estimator with average treatment effects on the treated (ATET) as

$$\tau_{ATET}^{PSM} = E_{P(X)|D=1}\{E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0, P(X)]\}. \tag{3.7}$$

Treated and untreated subjects having similar propensity scores, a balancing score, display similarly distributed pretreatment variables (Austin, 2011; Rosenbaum & Rubin, 1983). The use of a balancing score is appropriate for nonrandomized experiments where treatment and nontreatment units differ systematically. Rosenbaum and Rubin (1983) present five theorems identifying the conditions under which the propensity score is appropriate,[40] one of which affirms that if the treatment assignment is strongly ignorable given observed covariates ($X_i$), then the difference between the mean propensity score value for the treatment and control conditions yields an unbiased estimate of the average treatment effect. A treatment assignment is considered strongly ignorable when a) the treatment assignment is independent of the outcome given a vector of covariates; and b) each unit in the population has a chance of receiving the treatment (Rosenbaum & Rubin, 1983).

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[40] Rosenbaum and Rubin (1983, pp. 43-44), offers five theorems for governing the applicability of the propensity (balancing) score: (i) The propensity score is a balancing score. (ii) Any score that is 'finer' than the propensity score is a balancing score; moreover, x is the finest balancing score and the propensity score is the coarsest. (iii) If treatment assignment is strongly ignorable given x, then it is strongly ignorable given any balancing score. (iv) At any value of a balancing score, the difference between the treatment and control means is an unbiased estimate of the average treatment effect at that value of the balancing score if treatment assignment is strongly ignorable. Consequently, with strongly ignorable treatment assignment, pair matching on a balancing score, subclassification on a balancing score and covariance adjustment on a balancing score can all produce unbiased estimates of treatment effects. (v) Using sample estimates of balancing scores can produce sample balance on x.

Rosenbaum and Rubin (1983) further illustrate limitations with matching on more than a few covariates. As remedy to this limitation the propensity score is introduced as a scalar function of covariates “that summarizes the information required to balance the distribution of the covariates” (Rosenbaum and Rubin 1984, p. 516).

***Matching Metrics***

In this study, nearest-neighbor-style matching with replacement is used to derive the propensity score based on relevant covariates. *Nearest-neighbor* matching is accomplished as the pretreatment matching characteristics that most closely resemble one another are included and assigned a propensity score reflective of the closeness of the match. Further, if any given student is a closer match to another given a slightly different set of matching characteristics the more closely matching student may be a *replacement* for the less closely matched, resulting in one student potentially being represented in multiple matches. Given the sizes of the 2008 and 2009 high school graduation cohorts (each with approximately 45,000 students), the pool from which potential matches may occur is sufficiently large as to allow for virtually all matched sets to include perfect or near perfect matches and replacement becomes an element of the system with limited relevance.

As the propensity score represents the probability of assignment to the treated group, the matching methodology may be accomplished through either probit or logit style estimations. For this study, the probit estimation form was selected given the form’s handling of binary response variables ($Y_i$) such that there are two possible outcomes, which we will denote as 1 and 0. In this case, $Y_i$ represents the high school and higher education outcomes, most of which are measured as 0,1. We also have a vector of treatment variables ($X_i$), which are assumed to influence the outcome $Y$. The model then takes the form

$$\rho(Y = 1)|X = \Phi(\mathrm{X}'\beta), \tag{3.8}$$

where $\rho$ denotes probability, and $\Phi$ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The parameters β are typically estimated by maximum likelihood. It is possible to motivate the probit model as a latent variable model in the existence of an auxiliary random variable $Y^* = \mathrm{X}'\beta + \varepsilon_i$ where $\varepsilon \sim \mathrm{N}(0,1)$. Then $Y$ can be viewed as an indicator for whether this latent variable is positive:

$$Y = \begin{cases} 1 & if\ Y^* > 0\ i.e. -\varepsilon < \mathrm{X}'\beta \\ 0 & otherwise \end{cases} \tag{3.9}$$

The use of the standard normal distribution causes no loss of generality compared with using an arbitrary mean and standard deviation as adding a fixed amount to the mean can be compensated by subtracting the same amount from the intercept, and multiplying the standard deviation by a fixed amount can be compensated by multiplying the weights by the same amount. To see that the two models are equivalent, observe that

$$\rho(Y = 1)|X = \rho(Y^* > 0) = \rho(\mathrm{X}'\beta + \varepsilon > 0) \tag{3.10}$$

$$= \rho(\varepsilon > -\mathrm{X}\text{^}'\ \beta)$$

$$= \rho(\varepsilon < \mathrm{X}'\beta) \text{ (by symmetry of normal distribution)}$$

$$= \Phi(\mathrm{X}'\beta)$$

Once the propensity scores are calculated and matches are established they're balanced such that equal weighting is given to each type of match, even though there may be different numbers of matches for any given type.

***Unconfoundedness and Overlap***

The use of propensity score matching is conditioned on two assumptions: unconfoundedness and overlap (Caliendo & Kopeinig, 2005; Rosenbaum & Rubin, 1983). Unconfoundedness generically suggests the presence of a sufficient number of pretreatment covariates and outcomes such that, conditional on those controls, treatment assignment is essentially randomized. Unconfoundedness given the propensity score can be written as:

$$Y(0), Y(1) \parallel D | P(X), \forall X. \quad (3.11)$$

Not surprisingly, unconfoundedness is controversial; it aides us in ruling out self-selection based on unobservable variables. Further, unconfoundedness is fundamentally untestable, although in some cases there are ways to assess its plausibility or study sensitivity of estimates.

The second key assumption is overlap, which concerns the similarity of the covariate distributions for the treated and untreated student populations. The overlap assumption states that each individual has a positive probability of receiving each treatment level and plays a key role in any of the estimation methods based on unconfoundedness. In cases where parametric models are used, it may be easily overlooked. If overlap is weak, it may be necessary to redefine the subject population in order to precisely estimate a treatment effect on some subpopulation. The overlap assumption can be written as

$$0 < P(D = 1|X) < 1. \tag{3.12}$$

Plotting the estimated densities of the probability of receiving each treatment allows us to observe the overlap effect.

In this study, we're concerned with both unconfoundedness and overlap, which is the principal rationale behind employing propensity score matching methodology. The use of available demographic and pretreatment performance variables allows us to assert unconfoundedness, but it may be worth noting that in the estimation tables provided (Appendix D through M) only two cases present violations of the assumption. When the overlap assumption is violated, we can neither predict, nor account for, the unobserved outcomes for these students. The violation of the overlap assumption informs us that the estimated density has either too much mass or not enough in the regions in which they overlap.

Rosenbaum and Rubin illustrated the use of the propensity score to match treatment and control conditions in five subclassifications, following the recommendation of Cochran (1968). After finding the best-fit model using maximum likelihood estimation the balance of covariates within the five subclasses was scrutinized to ensure there are not systematic differences between the treatment and control conditions within each subclass. Once covariate balance was established, Rosenbaum and Rubin matched control and treatment cases and estimated the average treatment effect. Finally, to make a stronger case for the strongly ignorable treatment assignment assumption, sensitivity analysis was conducted which provides information about the credibility of the average treatment effect estimates (Rosenbaum & Rubin 1983, 1984).

### ***Estimation Models***

Propensity Score Matching analytics are not strictly regression estimates, but use either probit or logit forms to compute the propensity score, which are actually probabilities. If the outcome is continuous, the effect of treatment can be estimated as the difference between the mean outcome for treated subjects and the mean outcome for untreated subjects in the matched sample (Rosenbaum & Rubin 1983). If the outcome is binary, the effect of treatment can be estimated as the difference between the proportion of subjects experiencing the event in each of the two groups (treated versus untreated) in the matched sample. As such, the reporting of treatment effects can be done using the same metrics as are commonly used in randomized control treatments. The estimates report with coefficient, standard error, *P* value, and confidence intervals as do regressions estimates, but include a calculated *z* score instead of a *t* statistic to aid in inferring statistical significance and do not include an *r* squared value suggestive of the level of the model's fit.

Since this study considers several potential outcomes for each of two Utah public high school graduation cohorts and separately examines the effects of two unique and one combined treatment on each, the organization of the estimation models is relatively complex, even though the models themselves appear to be as simple as $Y = \beta_1 treatment + e$. However, this model is estimated for each match in the covariate set and it is only then that a coefficient, standard deviation, *z* score, probability, and confidence intervals are determined (see Figure 3.1). Appendix B presents the structure and outcomes of the complete panel of outcomes ( $Y$ ), treatments ( $t$ ), and matching covariates ( $X_1 .... X_n$ ) included in the examination of the effects of the treatments (Dual-Credit Enrollment and Early College High School) on the general population of students in the 2008 and 2009 Utah public high school graduation cohorts. Appendixes D through N present the similarly structured panels for these same cohorts and treatments, but focused on an examination of the average treatment effects on the treated among underrepresented students in the population. In each case, the examination yields the differences in outcomes based on the matched observations wherein two statistically similar students are considered, one of whom has selected treatment and the other of whom has not.

### ***Receiver Operating Characteristic (ROC) Analysis***

Receiver Operating Characteristic (ROC) Analysis quantifies the accuracy of diagnostic tests or other evaluation modalities used to discriminate between two states or conditions, allowing the discriminatory accuracy of a diagnostic test to be measured by its ability to correctly classify known subjects. As Propensity Score Matching's (PSM) model specification may be modified to include differing ranges of nearest neighbor matches, caliper adjustments with respect to the quality of potential matches, tolerance levels to fine tune the overlap assumption and the choice of probit or logit statistical forms, it isn't sufficient to employ the model offering the largest coefficients or "best outcomes," but to identify that model which yields the most accurate outcomes.[41] While basic regression models may rely heavily on *p* values, *t* statistics, *r* squared values, and a variety of model tests to infer or support model accuracy, only a few of these are available for use in PSM models. However, ROC analysis is built on a framework of a cluster of analyses and specifically assessing a model's accuracy by comparing the model's estimated outcomes for the cluster to the cluster's real outcomes by assigning *sensitivity* and *specificity* values, each between 0 and 1 (Metz 1978, Eng 2005, Fawcett 2006). *Sensitivity*, also referred to as the *true positive rate*, is the ratio of *true positives* to *total positives*, and *specificity* is the ratio of *true negatives* to *false positives* plus *true negatives*. As *false positives* plus *true positives* equal 1 or 100%, *specificity* is also referred to as *1-false positive rate*.

As propensity score matching models are designed to be built around a treatment as a binary state (applied or not) with a binary outcome (experienced or not), ROC analysis's use of *sensitivity* and *specificity* is well aligned with the analytical method. However, where continuous outcome variables are present the potential outcomes must be separated into binary groups; otherwise the application of ROC analysis is questionable (Eng, 2005; Fawcett, 1978; Metz, 2005).

As this study considers the potential effects of a treatment on a given outcome we can visualize *sensitivity* and *specificity* through the confusion matrix in Figure 3.2 in

[41] Nearest Neighbor, Caliper, Tolerance and Form are adjustable specifications used in propensity score matching. Nearest Neighbor specifies the number of matches per observation, Caliper specifies the maximum distance at which two observations are a potential match. Tolerance specifies the minimum acceptable propensity score to be included. STATA's default parameters include Nearest Neighbor: 1; Caliper: all observations are potential matches regardless of how dissimilar they are; Tolerance: 1e-5; Form: probit.

which the outcome of a given treatment is estimated as providing either a positive or negative effect on a given student for which there is observational data as to whether the actual effect is also either positive or negative. Applying this framework to a cluster of students using a given model allows us to form *sensitivity* and *specificity* values.

Were we to plot *sensitivity* and *1-specificity* in X,Y space we would visualize the range in which we would expect an ROC curve based on informed analysis. In this form, a line beginning at 0,0 and moving upwards to 1,1 with a constant slope of 1 becomes synonymous with a *random guess* for which the estimated state is as often accurate as it is not. Analysis yielding perfect results would yield a curve moving from 0,0 upwards to 0,1 and then directly to 1,1 as seen in Figure 3.3. Given that *specificity = 1- false positive rate*, we can also say the *false positive rate = 1- specificity*, which aids in forming a graphic to further visualize this relationship between *sensitivity* and *specificity* in X,Y space in which *sensitivity* or the *true positive rate* is measured (0-1) on the Y axis and the *false positive rate* or *1-specificity* (0-1) is measured on the X axis.

Based on the presumption that the propensity score matching estimate is likely to offer accurate results more often than those that are inaccurate, this form will also form a concave curve with a monotonically upward slope above the line representing the *random guess* as in Figure 3.4, which curve is the *ROC Curve*. This yields a measurable area under the curve (AUC) with a value greater than .50 and less than or equal to 1.0. The greater the area under the curve, where the ROC curve is further from the *Random Guess* line, the more accurate the model. An area under the curve of 0.50

suggests a model no better than simple guessing, while an AUC 1.0 suggests a perfectly accurate model.

This relationship can also be visualized by considering normal distributions for *sensitivity* and *specificity*. The area under each curve represents *true negative* and *true positive* space, respectively, with the area representing the overlap of the curves being *false negative/false positive* space. An optimal model is then represented by the smallest possible *false negative/false positive* space and a *cutoff line* splitting that space as equally as possible (Figure 3.5). By changing the model specifications we observe shifts in a *cutoff line* where shifts to the right increase *specificity* but decrease *sensitivity* and shifts to the right increase s*ensitivity*, but decrease s*pecificity* (Figure 3.6). These shifts and changes in the relative size of the *false positive/false negative* space correspond to changes in the AUC of the ROC curve and are the result of changes in the nearest neighbor, caliper, tolerance settings, and use of the probit or logit form in the propensity score model.

Visualizing the application of ROC analysis for a particular model based on variations in model specification is shown in Figure 3.8, using the effects of Dual-Credit Enrollment (DCE) on K12 Graduation (K12 GRAD) for the 2008 high school graduation cohort with variations in pretreatment variables and Nearest Neighbor matches. As this particular model, one of many in this study, may be used to examine student outcomes based on a combination of eight pretreatment variables and three Nearest Neighbor match levels, there are nearly 241,000 possible models available, each separable into clusters resulting in separate combinations of *sensitivity* and *specificity,* with each combination forming a point on a ROC curve (Figure 3.9) and yielding an area under the curve (AUC). For this study we include each of the three high school performance variables (CRT scores for Science, Language Arts, and Algebra I) in each model variation and select combinations of Gender, Minority, Income, Mobile, ELL and Nearest Neighbor match in 10 model variations (Figure 3.10) resulting in different values for each area under the curve (AUC) and yielding separate ROC curves for each model such that a set of ROC curves may be plotted and the optimal curve, is revealed as Model A.4, excluding the mobility variable (present in some 40% of observations) and employing Nearest Neighbor matching equal to 1.

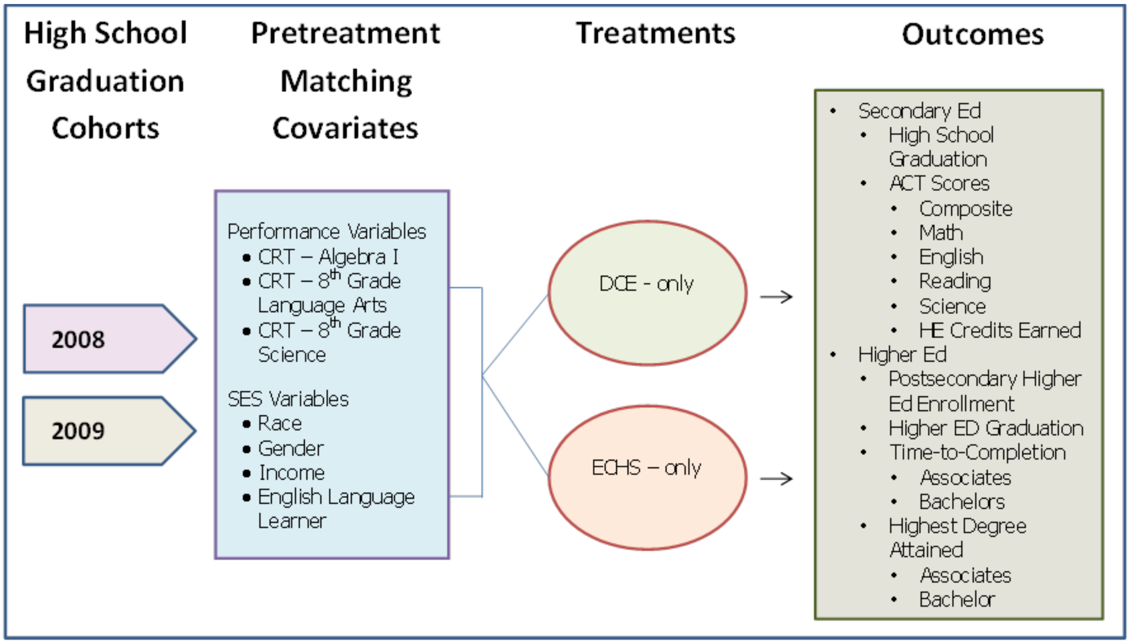


**Figure 3.1 Propensity Score Matching Model**

**ROC Confusion Matrix**

| | | **Observed State** | |
|---|---|---|---|
| | | Positive | Negative |
| **Estimated State** | Positive | ***True Positive*** | ***False Positive*** |
| | Negative | ***False Negative*** | ***True Negative*** |

$$sensitivity = \frac{true\ positives}{total\ positive}$$

$$= true\ positive\ rate$$

$$specificity = \frac{true\ negatives}{false\ positives + true\ negatives}$$

$$= 1 - false\ positive\ rate$$

$$false\ positive\ rate = 1 - \text{specificity}$$

$$accuracy = \frac{true\ positives + true\ negatives}{total\ positives + \text{total}}$$

**Figure 3.2 ROC Confusion Matrix**

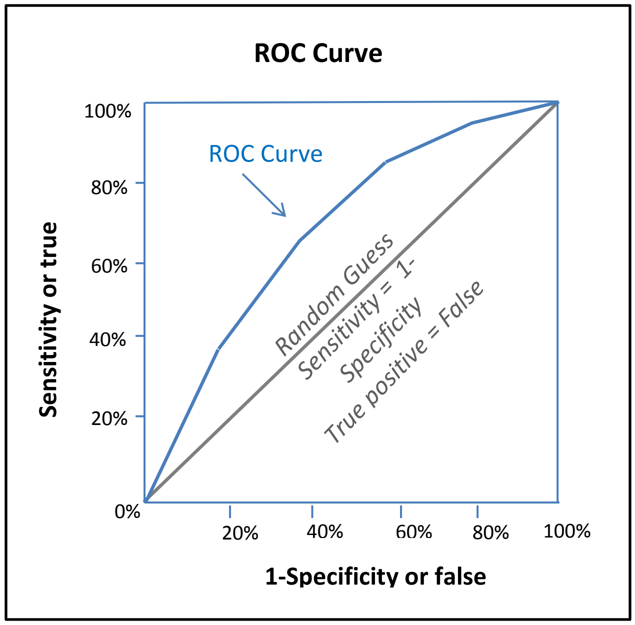


**Figure 3.3 ROC Curve**

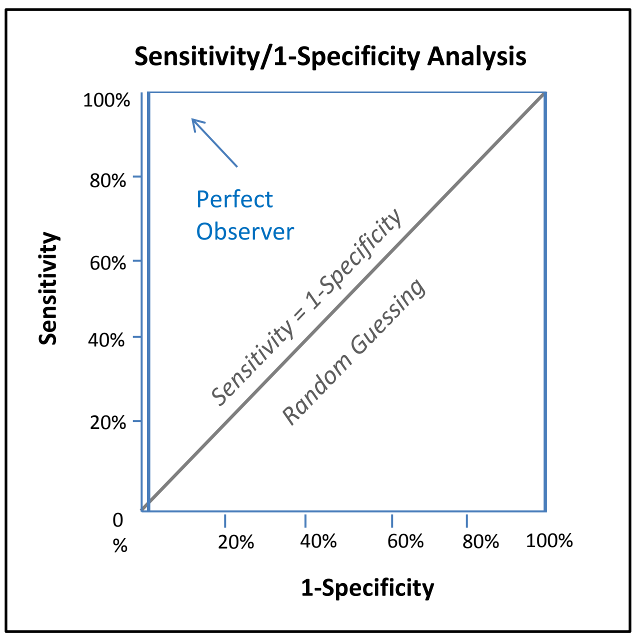


**Figure 3.4 Sensitivity/1-Specificity Analysis**

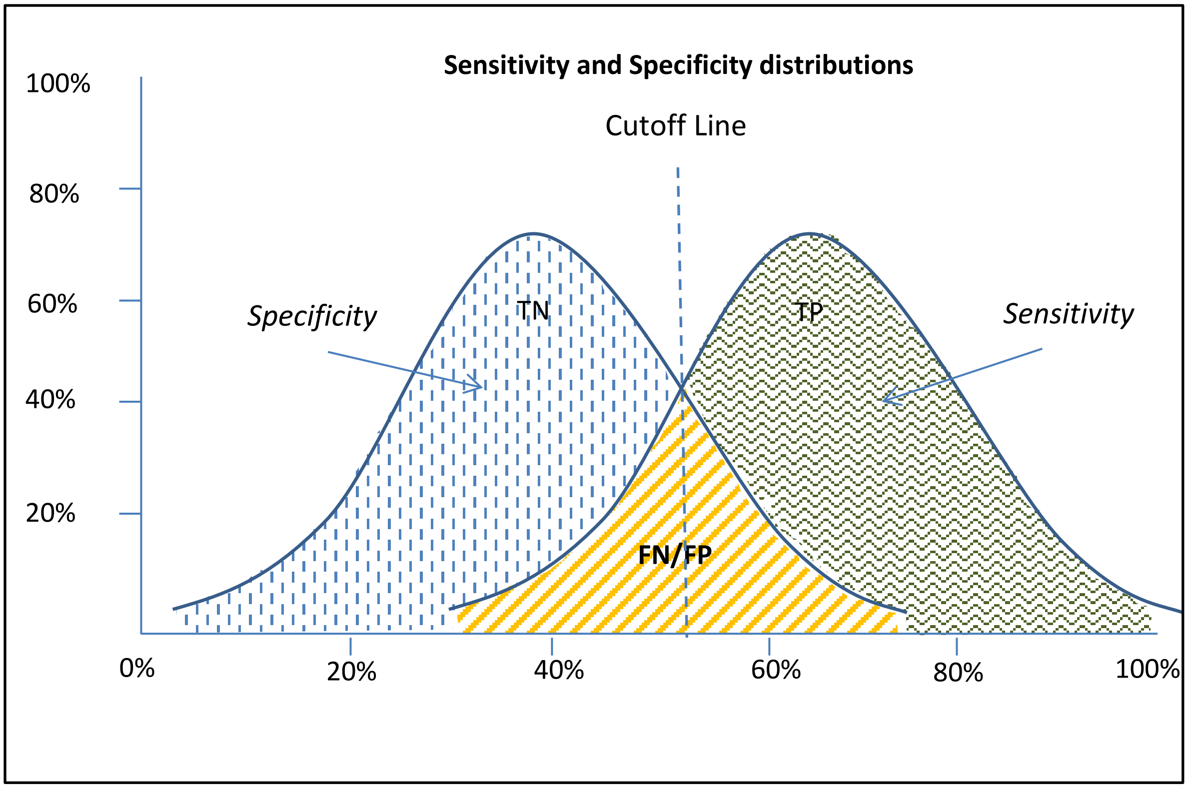


**Figure 3.5 Sensitivity and Specificity Distributions**

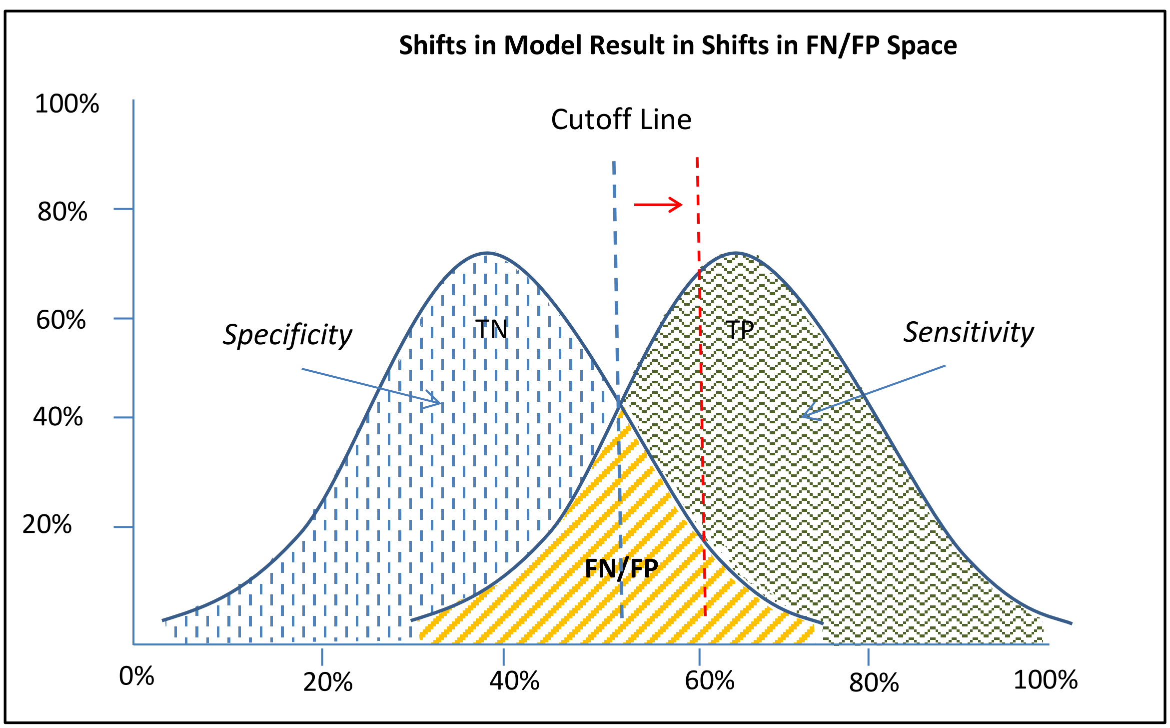


**Figure 3.6 Shifts in Model Result in Shifts in FN/FP Space**

**Confusion Matrix: Effects of DCE on K12 GRAD (2008 Cohort)**

| | | Observed State: Graduated | Observed State: Not Graduated |
|---|---|---|---|
| Estimated State | Graduated | ***True Positive*** | ***False Positive*** |
| | Not Graduated | ***False Negative*** | ***True Negative*** |

**Figure 3.7 Confusion Matrix: Effects of DCE on K12 Graduation**

**Model Cluster**
**Effects of Dual-Credit Enrollment (DCE)**
**on K12 graduation (K12 GRAD)**

| Outcome | Treatment | Pretreatment Variables | Nearest Neighbor |
|---|---|---|---|
| K12 GRAD | DCE | CRT - Science | 1 |
| | | CRT – Language Arts | 2 |
| | | CRT _ Algebra I | 3 |
| | | Income | |
| | | ELL | |
| | | Gender | |
| | | Minority | |

**Figure 3.8 Model Cluster Effects of Dual Credit Enrollment (DCE) on K12 Graduation**

**Model Specification Variations**
**Effects of Dual-Credit Enrollment (DCE) on K12 graduation (K12 GRAD)**

| Model | Pretreatment Exclusions | | | | | Nearest Neighbor | Form | AUC |
|---|---|---|---|---|---|---|---|---|
| | Mobile | Income | ELL | Gender | Minority | | | |
| A.1 | | | | | | 1 | Probit | 0.681 |
| A.2 | | | | | | 2 | Probit | 0.360 |
| A.3 | | | | | | 3 | Probit | 0.631 |
| A.4 | X | | | | | 1 | Probit | 0.787 |
| A.5 | X | | | | | 2 | Probit | 0.768 |
| A.6 | X | | | | | 3 | Probit | 0.519 |
| A.7 | X | X | | | | 1 | Probit | 0.786 |
| A.8 | X | | X | | | 1 | Probit | 0.778 |
| A.9 | X | | | X | | 1 | Probit | 0.785 |
| A.10 | X | | | | X | 1 | Probit | 0.779 |

**Figure 3.9 Model Specification Variations**

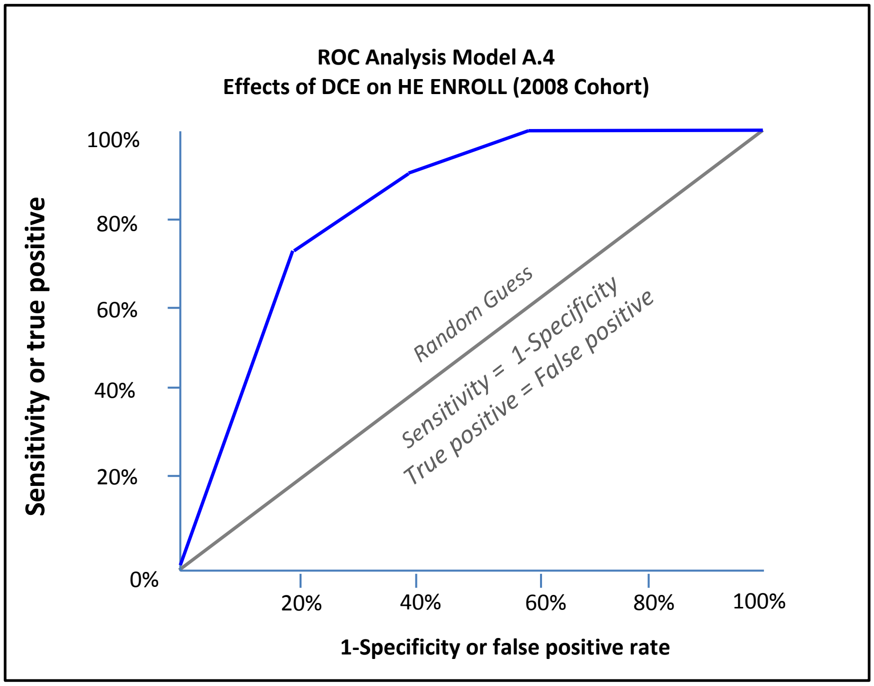


**Figure 3.10 ROC Analysis Model A.4**

# 4. DATA DEVELOPMENT

This study employs individual level education data obtained through the Utah Data Alliance[42] via data sources originating with the Utah State Office of Education, Utah System of Higher Education, and National Student Clearinghouse (NSC[43]). Access to these data was provided through a secured data lab within the Utah Education Policy Center and is the result of the education data mining activities of the Utah Data Alliance and its partners. This data set offers the ability to track students through their public primary, secondary, and higher education careers. The Utah Data Alliance also brings in limited data regarding higher education enrollment and graduation outside of Utah public education from the National Student Clearinghouse, though the NSC is not a partner in the alliance. This makes possible an evaluation of the effects of each high school career path: Traditional, Dual-Credit Enrollment, and Early College High School. The consideration of such an evaluation offers relevant data to support public policy

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[42] Data for this research were accessible through Utah's state longitudinal data system database administered by the Utah Data Alliance (UDA) which includes data supplied by UDA partners and the StudentTracker service from the National Student Clearinghouse. This research including the methods, results, and conclusions neither necessarily reflect the views nor are endorsed by the UDA partners. All errors are the responsibility of the author.

[43] The National Student Clearinghouse helps educational institutions improve efficiency, reduce costs and workload, and enhance the quality-of-service they provide to their students and alumni, lending institutions, employers, and other organizations. The organization provides services as an aligned agent to participating institutions, supporting their administrative, student access, accountability, and analytical needs. http://www.studentclearinghouse.org/

towards more efficient economic and temporal public education investments in support of improved outcomes.

Data collected for the targeted high school graduation cohorts include available public education data for Utah students through the end of the 2012/2013 academic year. It may be important to note that these data are reflective of the Utah public high school experiences of these cohorts, but their higher education experiences are ongoing and future data releases may result in slight changes in outcomes. As of the 2013 UDA data release, the 2008 high school graduation cohort had reached its 5-year high school graduation anniversary, but had yet to arrive at the 6-year anniversary considered by some to be the gold standard for assessing higher education graduation rates (Gold & Albert, 2006; Scott, Bailey, & Kienzl, 2006); the 2009 high school graduation cohort had reached its 4-year anniversary. Given the expected temporal advantage earned by high school graduates through participation in dual-credit programs, the traditional expectation of a 4-year higher education experience for students pursuing a Bachelor's Degree, and the lack of universal recognition of the 6-year time frame as a "gold standard," this study examines secondary and higher education outcomes 4 years after high school graduation for each of the 2008 and 2009 high school graduation cohorts, but contains notes with respect to outcomes after the 5$^{th}$ year for the 2008 cohort. Dual-credit enrollment's potential temporal advantages aid in forming expectations of observable higher education outcomes as early as Spring 2010 for the 2008 cohort and 2011 for the 2009 cohort – well within the 4-year period examined in the study.

Partners in the Utah Data Alliance contribute significant quantities of data to this effort each year, with the data for a given academic year, ending in June, being made available the following spring. This amounts to millions of observations per year and the task of converting these data into a useful form for public education research is significant.

To obtain the data used in this study, it was necessary to present a proposal to the Utah Data Alliance, complete with University of Utah Institutional Review Board approval[44] in October of 2013, for which approval to begin working with the individual level student data was received in late November of the same year. With the assistance of the Utah Data Alliance staff, and programming support from the Utah Education Policy Center and Utah Education Network, data sets for each of the targeted cohorts were culled (see Appendix O for a detailed discussion of data preparation) and made available across a secured network operating from within a second tier secured server environment housed within the confines of the Utah Data Alliance offices and the University of Utah, College of Education. This bilevel secured server/network structure underlies the import the UDA and its partners place on security with respect to student level data. Prior to release for research activities, the individual level student data are scrubbed of obvious student identification markers, but are assigned and retain a unique identification number. The required data security plan conforms to Federal

[44] University of Utah Institutional Review Board (IRB) approval #00063312 granted 10/23/2013

Educational Rights and Privacy Act (FERPA)[45] regulations and restrictions, amongst which are that output of data analysis for which individual observations are less than 10 ($n$ <10) or outcome is equal to 100% may not be reported and must be suppressed. Further, the data cultivation, management, analysis and output functions performed within the secured server environment must be reviewed by Utah Data Alliance staff for FERPA, Utah Education Policy Center and Utah Data Alliance compliance prior to being exported from the secured network.

## Study and Data Limitations

This study is expressly restricted to the experience of Utah public high school students through their secondary and higher education careers; it represents the Utah case with respect to the effects of Dual-Credit Enrollment and Early College High School. Other studies using the National Education Longitudinal Study of 1988 and the Education Longitudinal Study of 2002 provide insights into the secondary and higher education effects of dual-credit enrollment, but lack necessary data details to separate Dual-Credit Enrollment from Early College High School programs. These studies do, however, include data points measuring important noneducation variables, such as household income, parental and sibling education levels, etc. not resident in the Utah data. Were these data sets able to be linked, they would represent an enviable data source capable of producing results yet stronger than either set provides independently, but such linkage is not available at this time nor is it expected to be in the future.

[45] The Family Educational Rights and Privacy Act (FERPA) (20 U.S.C. § 1232g; 34 CFR Part 99) is a Federal law that protects the privacy of student education records. The law applies to all schools that receive funds under an applicable program of the U.S. Department of Education.

Efforts to link the Utah data to other data sets rich with demographic variables are under consideration, and may be the subject of future research efforts.

The data available for this study through the Utah Data Alliance and the Utah Education Policy Center are limited to student-level data for Utah public education for those students included in the 2008 and 2009 high school graduation cohorts. The higher education data are limited to Utah public high school participants and do not include students who may have been home schooled and opted for a General Educational Development certificate (GED) and those participating in private education. Further, the higher education and enrollment data brought in through the National Student Clearinghouse only provides limited higher education enrollment and graduation data for those students who were part of Utah public primary and/or secondary education, but who chose to participate in higher education outside of the Utah System of Higher Education (USHE).

The available data are those which are collected via Utah public education institutions, principally taken from registration, enrollment, course-level student participation and performance, and do not include data with respect to the students' household other than indicators of household income status, mobility, and English second language. The data also contain date of birth, gender and race variables for each student; however, the race variable is specific to the student and is not necessarily reflective of the household from which the student comes. The data contain no variables or markers to indicate parental or sibling education, but the respective K12 Higher Ed tables do contain a variable for higher education degree intentions. Like the

GPA and various credit hours variables available in this same table, the higher education degree intent variable is inconsistent and unreliable in its current form, but may be reevaluated for use in future studies in the event that future data releases improve the accuracy of these data points.

That students must take proactive steps to participate in Dual-Credit Enrollment or Early College High School programs yields unavoidable concern in respect to selection bias and motivates further investigation into the resultant endogeneity between independent and dependent variables. In consideration of this challenge, an examination of various factors potentially revealing the effects of such bias are included. It is expected that those students most likely to self-select into the examined treatments (Dual-Credit Enrollment and Early College High School) may also be those who experience increased high school graduation rates, higher education participation, lower time-to-completion, higher rates of degree completion and attainment, and increased labor market effects.

To ascertain if this relationship is present in the observed student populations, this study employs a quasiexperimental design methodology, Propensity Score Matching, but the lack of potentially relevant household variables from which to make appropriate matches results in what must be accepted as only a diminished level of endogeneity bias, rather than a completion removal of the bias effect. Though Propensity Score Matching offers a pathway towards assigning causality, as an estimator its strength is reliant on the existence of complete and quality matching variables, which are limited in the Utah education longitudinal data sets. As such, causality may be less than certain, though the methodology's outcomes remain interesting and useful.

Chapter 3 on Methodology provides a visual representation of the causal chain underlying the data in this study (Figure 3.3), inclusive of the pretreatment matching function of the Propensity Score Matching methodology employed.

## Utah High School Graduation Cohorts: 2008 and 2009

Utah's public education high school graduation cohorts of 2008 and 2009 include 45,214 and 45,328 students, respectively, of which 29,061 and 20,056 received a high school diploma in the prescribed time frame. Of the combined cohorts, 52% are male, 48% female, 21% minority, 41% low income, and 12% English Language Learners. Among those who graduated, the distributions change to 50% male, 50% female, 14% minority, 32% low income and 8% English Language Learners.

The distributions change when differentiated by treatment with participation in ECHS representing just 2.2% of the combined high school graduation cohorts and DCE representing 34.6%. Though these programs are expected to be targeted to underrepresented students, program participation differentiated by socio-economic factors suggests the state has significant work to do. The socio-economic status of ECHS and DCE participants does not mirror that of the high school graduation cohorts from which they come. We see that socio-economic status of the respective cohorts are relatively homogenous, but when the treatments are compared to an average of the cohorts we see meaningful differences; each treatment includes lower male, minority, low income, and English Language Learner (ELL) populations than the average cohort and higher female components.

This leaves the TRAD (control group) students with higher male, low income, and ELL and lower female representation than the average cohort (Figure 4.1[46]). We see that the cohort average is comprised of 79% White, 14% Hispanic, with Black, Asian, Pacific Islander, Multirace and American Indian students each representing 2% or less (Figure 4.2[47]). By contrast, DCE and ECHS program enrollments have higher White and Asian populations and yet lower Black, Hispanic, Pacific Islander, Multirace and American Indian participation.

The measures for high school and higher education enrollment and graduation echo disparities observed across the nation. While high school enrollment and graduation present a near even distribution between males and females, higher education statistics present a picture relatively evenly distributed in respect to enrollment, but more heavily weighted towards females in respect to graduation (Figure 4.3[48]). We begin to see hints of (2008 and 2009), 85.7% of the high school graduates, 86.7% of the higher education enrollees, and 89.8% of the higher education graduates, without regard to the type of higher education degree earned. We further see disparate levels of degree attainment, Associate’s and Bachelor’s Degrees, but with similar distributions as higher education degree attainment.

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[46] Figure 4.1: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[47] Figure 4.2: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[48] Figure 4.3: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

Minimal disparity exists in higher education enrollment as enrollments trend towards females with an average ratio of males to females of 49:51.

This ratio changes dramatically to 30:70 upon higher education graduation, due largely to the changing national trend towards female higher education enrollment and graduation, but may also be affected by Utah's high Latter-Day Saint (LDS) population[49] and the number of years of higher education data examined in this study (5 years for the 2008 cohort and 4 years for 2009).

When broken down by racial composition, we see an increasing percentage of White students moving from high school enrollment to high school graduation, higher education enrollment, and higher education graduation. White students represent only 79.2% of high school enrollees in the observed cohorts earning 91.3% of the Associate's Degrees and 90.2% of all Bachelor's Degrees (Figure 4.4[50]). These values are slightly greater than the White student distribution with respect to higher education degree attainment due to the presence of multiple degree holders (Associate's and Bachelor's) in the observed cohorts. Consistent with the expected findings for ECHS and DCE we see that participants in these programs have high graduation rates of 94% and 93.9% respectively, compared to a rate of 50.1% for TRAD students and 66.5% for the high school graduation cohorts combined.

[49] Many LDS males voluntarily postpone or take leave of higher education for a period of 2 years between the ages of 18-22 years old. Prior to the 2013-2014 academic year LDS females participation in such voluntary service began at age 21 and likely provides limited impact on the subject cohorts. Though detailed figures are not available, the numbers are thought by Utah System of Higher Education officials to be sufficiently large as to impact the timing of higher education enrollments and higher education time-to-completion statistics.

[50] Figure 4.4: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

Utah public higher education enrollment (USHE), non-USHE higher education enrollment, and public and private higher education enrollments include any higher education enrollments for the targeted high school graduation cohorts and are calculated differently than are the outcome variables for *Postsecondary Higher Education Enrollment – Utah* and *Postsecondary Higher Education Enrollment – All* (Figure 4.5[51]) In the event that a cohort member enrolled in Utah public higher education and then also enrolled in higher education outside of Utah or at a private institution in Utah, two enrollments are counted. The *Postsecondary Higher Education Enrollment* outcome variables observe the first postsecondary higher education enrollment and do not consider subsequent enrollments.

Utah public higher education enrollments comprised 77.4% of the enrollment in all higher education for the targeted cohorts generally, while representing 79.7% of the enrollments for ECHS students, 77.5% for DCE students and 69% for TRAD students. The differences between TRAD and dual-credit enrollment students, generally, may be a function of dual-credit enrollee's accumulated investment in higher education credit hours, but the relationship between accumulated credit and Utah public higher education enrollment is somewhat ambiguous. Were the relationship clear and consistent, ECHS participants with higher levels of accumulated credits would be expected to have a higher rate of enrollment in Utah public higher education than Dual-Credit Enrollees, but the opposite is observed.

[51] Figure 4.4: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

With respect to enrollment in public versus private higher education we see that public higher education enrollments comprised 80.7% of all higher education enrollments for the targeted cohorts, while representing 82.8% of ECHS public higher education enrollments and 92.4% and 82.4% for DCE and TRAD students, respectively.

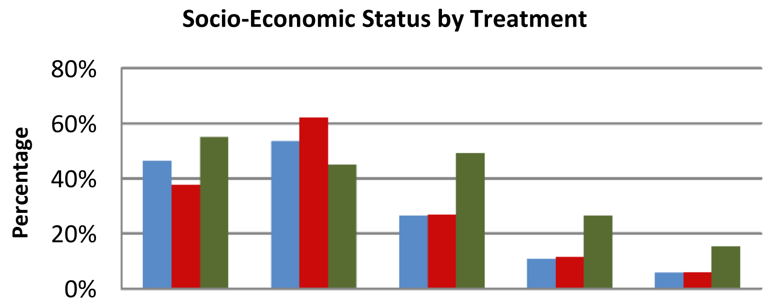
The statistics for higher education graduation show that ECHS participants experience 90.2% of their combined higher education graduations in the Utah System of Higher Education (USHE) while DCE and TRAD students experience 64.6% and 48.9%, respectively. This is consistent with what we know of these students as a high portion of ECHS students graduate from high school coincident with earning an Associate's Degree through USHE. The difference in USHE graduations for DCE and TRAD students is consistent with the higher education enrollment pattern observed; a lesser percentage of TRAD students enroll in and graduate from USHE than do Dual-Credit Enrollees.

We see that 37.7% of ECHS students' higher education graduations include Bachelor's Degrees, while DCE and TRAD students earn Bachelor's Degrees, 41.9% and 45.3%, respectively. While ECHS and DCE students only represent 2.2% and 34.7% of the combined high school graduation cohorts, they earned 11.9% and 66.7% of the Associate's Degrees, respectively, and 9.6% and 65.8% of the Bachelor's Degrees. This isn't unexpected due to the timing of the collected data and the temporal advantage offered these students, but is a confirmation of the effects of the treatments. A review of average Time-to-Completion for an Associate's (Avg T2C Assoc) and/or Bachelor's

Degree (Avg T2C BACH), inclusive of both the 2008 and 2009 cohorts, yields modest differences between the considered racial groups (Figure 4.6[52]).

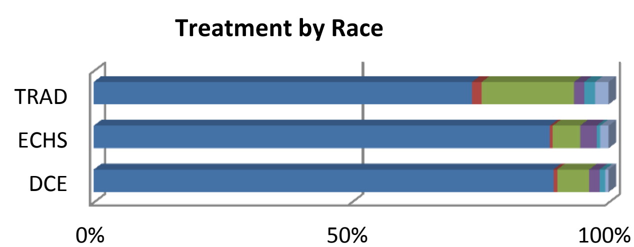
White students experience the lowest mean days to Associate's and Bachelor's Degree completion: 906.56 and 1481.38 days, respectively. Though the mean days to Associate's Degree completion among the various races differs by more than 423 days, the same measure for Bachelor's Degree completion differs by only 193.2 days: The temporal advantage White students experience diminishes between the attainment of the two types of degrees.

[52] Figure 4.6: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release



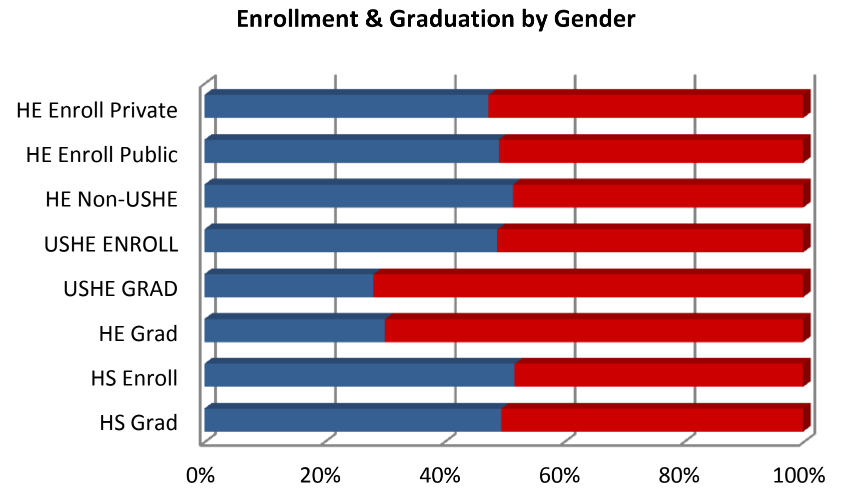

| | Male | Female | Low Income | Minority | ELL |
|---|---|---|---|---|---|
| DCE | 46% | 54% | 27% | 11% | 6% |
| ECHS | 38% | 62% | 27% | 11% | 6% |
| TRAD | 55% | 45% | 49% | 27% | 15% |

**Figure 4.1 Socio-Economic Status by Treatment**



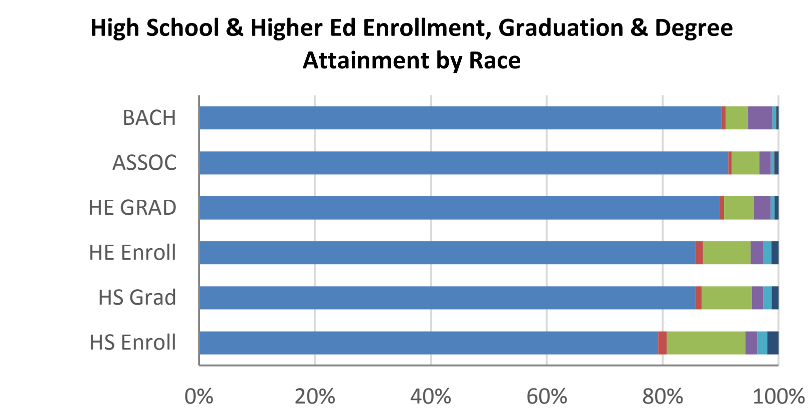

| | DCE | ECHS | TRAD |
|---|---|---|---|
| Caucasian | 89.2 | 88.5 | 73.4 |
| Black | 0.7 | 0.6 | 1.9 |
| Hispanic | 6.2 | 5.3 | 17.9 |
| Asian | 2.0 | 3.2 | 2.0 |
| Pacific Islander | 1.0 | 0.7 | 2.1 |
| Amer Indian | 0.7 | 1.7 | 2.6 |

**Figure 4.2 Treatment by Race**



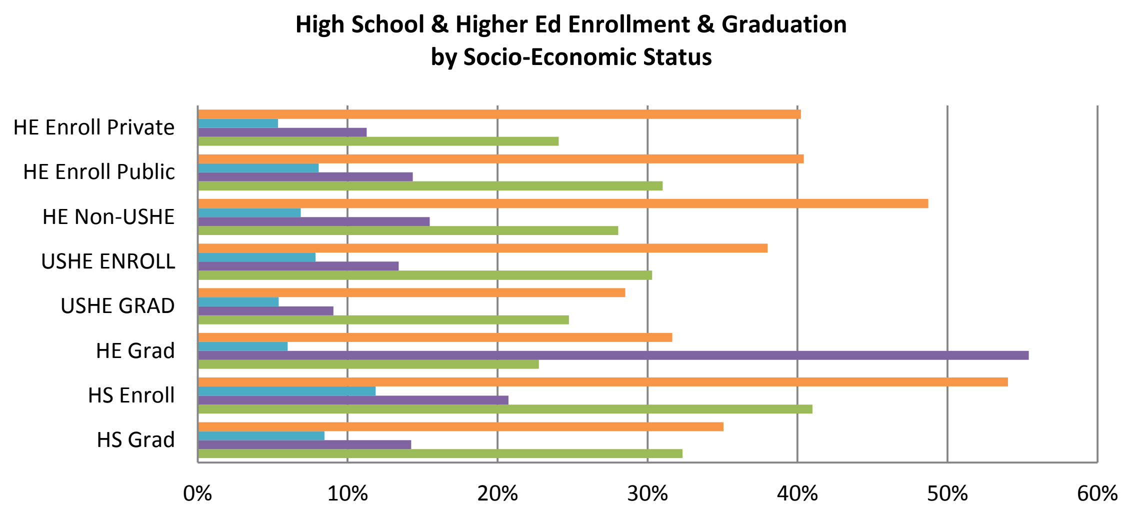

| | HS Grad | HS Enroll | HE Grad | USHE GRAD | USHE ENROLL | HE Non-USHE | HE Enroll Public | HE Enroll Private |
|---|---|---|---|---|---|---|---|---|
| Male | 50% | 52% | 30% | 28% | 49% | 51% | 49% | 47% |
| Female | 50% | 48% | 70% | 72% | 51% | 49% | 51% | 53% |

**Figure 4.3 Enrollment & Graduation by Gender**



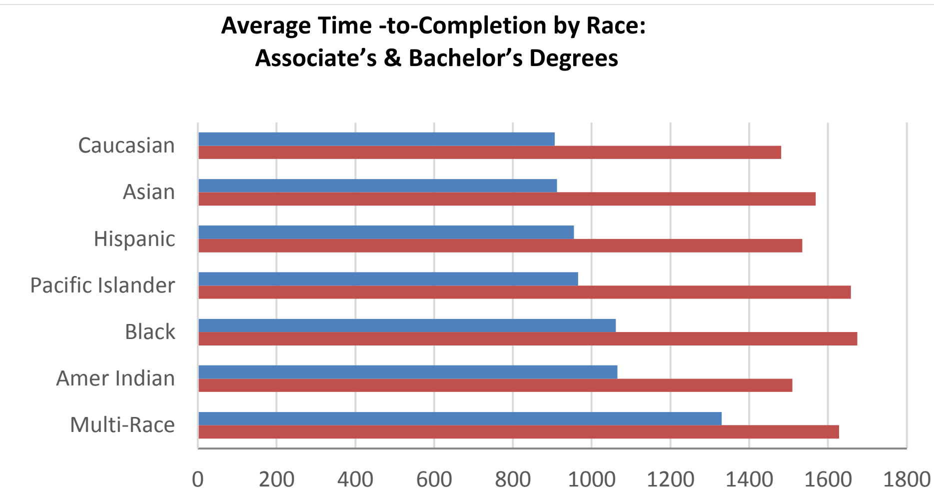

| | HS Enroll | HS Grad | HE Enroll | HE GRAD | ASSOC | BACH |
|---|---|---|---|---|---|---|
| Caucasian | 79.2 | 85.7 | 85.7 | 89.8 | 91.3 | 90.2 |
| Black | 1.5 | 1.0 | 1.2 | 0.7 | 0.6 | 0.7 |
| Hispanic | 13.6 | 8.7 | 8.2 | 5.2 | 4.8 | 3.8 |
| Asian | 2.0 | 1.9 | 2.2 | 2.9 | 2.0 | 4.2 |
| Pacific Islander | 1.7 | 1.5 | 1.4 | 0.7 | 0.6 | 0.7 |
| Multi-Race | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Amer Indian | 1.9 | 1.2 | 1.2 | 0.7 | 0.7 | 0.4 |

**Figure 4.4 High School & Higher Ed Enrollment, Graduation, & Degree Attainment by Race**




| | HS Grad | HS Enroll | HE Grad | USHE GRAD | USHE ENROLL | HE Non-USHE | HE Enroll Public | HE Enroll Private |
|---|---|---|---|---|---|---|---|---|
| Mobile | 35% | 54% | 32% | 29% | 38% | 49% | 40% | 40% |
| ELL | 8% | 12% | 6% | 5% | 8% | 7% | 8% | 5% |
| Minority | 14% | 21% | 55% | 9% | 13% | 15% | 14% | 11% |
| Low Income | 32% | 41% | 23% | 25% | 30% | 28% | 31% | 24% |

**Figure 4.5 High School & Higher Ed Enrollment & Graduation by Socio-Economic Status**




| | Multi-Race | Amer Indian | Black | Pacific Islander | Hispanic | Asian | Caucasian |
|---|---|---|---|---|---|---|---|
| Avg T2C ASSOC | 1330 | 1065 | 1061 | 966 | 955 | 912 | 907 |
| Avg T2C BACH | 1628 | 1510 | 1675 | 1658 | 1535 | 1569 | 1481 |

**Figure 4.6 Average Time-to-Completion by Race: Associate and Bachelor Degrees**

# 5. GENERAL STUDENT POPULATION RESULTS

Of interest in this study is whether or not participation in Dual-Credit Enrollment (DCE) or Early College High School (ECHS) as treatments on student populations provides students with measurable differences in high school graduation and performance, postsecondary higher education enrollment, and higher education graduation, time-to-completion and degree attainment. This section deals with the results of these two treatments, both separately and collectively, in respect to the *General Population* of students in the Utah high school graduation cohorts of 2008 and 2009. The results of the Propensity Score Matching (PSM) analytics are the average treatment effect on the treated (ATET) and read in much in the same manner as results for any standard statistical estimations with three exceptions: 1) Where both the independent and dependent variables are binary, the resulting coefficients represent the treated population's increased (or decreased) probability of experiencing the outcome compared to those in the control group; 2) there is no *r* squared value when dealing with PSM; and 3) statistical significance is measured through a *z* score rather than a *t* statistic (Austin, 2011; Peikes, Moreno, & Orzol, 2012), as noted in the section on Methodology. Where the outcome variable is continuous, the resulting coefficient represents the change in the outcome for the treated population compared to the control group.

The results are considered in three different groupings: 1) *high school graduation and performance*, 2) *postsecondary higher education enrollment and graduation measurements* and 3) *degree attainment and time-to-completion*. In each case, the treatments are taken individually for Dual-Credit Enrollment (DCE) and Early College High School (ECHS), and as an aggregated treatment (General) reflecting the condition that ECHS is a form of the more generalized dual-credit enrollment. Also, in the case of the high school graduation and performance and postsecondary higher education enrollment each of the three targeted cohorts is measured separately, but also collectively. This is the result of participation in high school being historical for the subject students and an expectation that most of those students who are likely to enroll in higher education will have already done so, as the data for this study are collected and reported some 4 to 6 years after their high school graduations (Gold & Albert, 2006; Scott, Bailey, & Kienzl, 2006). All other outcome variables are measured for each individual cohort reflective of the ongoing higher education experience of many of these students. In several cases (< 1% of the outcomes) the Propensity Score Match returned an overlap assumption error.

## High School Graduation and Performance

The measurements of DCE and ECHS in respect to high school graduation and performance include variables representing K12 graduation (binary) and ACT test score measures for the Composite, Math, Reading, English and Science test scores (continuous). The estimations for these outcomes include DCE, ECHS, and combined dual credit enrollment (General) treatments, each of which is estimated for the high school graduation cohorts of 2008 and 2009 separately and in the aggregate.

The measures for Dual-Credit Enrollment and Early College High School in respect to high school graduation and performance include variables representing K12 graduation (binary) and ACT test score measures for the Composite, Math, Reading, English and Science test scores (continuous). The estimations for these outcomes include Dual-Credit Enrollment (DCE), Early College High School (ECHS), and combined dual credit enrollment (General) treatments, each of which is estimated for the high school graduation cohorts of 2008 and 2009 separately and in the aggregate.

*K12 Graduation* (Figure 5.1[53]): This examination offers an estimation of the effects of Dual-Credit Enrollment and/or Early College High School (treatments) on high school graduation experience of students in the Utah public education high school graduation cohorts of 2008 and 2009. As presented in Appendix D, each of the estimations for high school graduation is statistically significant below the 1% level with coefficients ranging from 0.198 to .247. We see that the average treatment effect on the treated for both Dual-Credit Enrollment and Early College High School, individually and in the aggregate, results in an increased probability of high school graduation for the treated population of between 19.8% to 24.7%. Interestingly, there is not a substantial difference between the effects of the differentiated treatments.

K12 graduation rates in the state of Utah are already high in relation to other states generally (Greene & Forster, 2003) and specifically in relation to state level per

[53] Figure 5.1: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

pupil expenditures. The estimates for K12 Graduation present statistically significant improvements for each treatment variant ranging from a low average treatment effect on the treated of 19.8% for the ECHS students in the 2009 cohort to a high of 24.7% experienced for the Dual-Credit Enrollment students in the 2008 cohort.

*ACT test score measures* (Figures 5.2[54], 5.3[55] and 5.4[56]): For the observed high school graduation cohorts, ACT examinations were administered during the winter semester of the 11th grade, at central locations, without charge to the student, and outside of regular school hours. As such, participation in ACT testing is voluntary and likely only selected by those students who expect to attend some form of higher education: of the 90,593 students in the target graduation cohorts, 36,189 took the complete exam panel.[57] A separate Ordinary Least Squares (OLS) regression[58] was performed for the combined high school graduation cohorts with the results presenting a statistically significant and positive correlation between the each of the test scores and both high school graduation and higher education enrollment.

There is not a substantial difference between the effects of the differentiated treatments; each offering changes in students' various ACT test scores of less than 1.35 points from a score range of 1–36. Recall that the ACT exam scores used in this study

[54] Figure 5.2: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[55] Figure 5.3: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[56] Figure 5.4: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[57] The complete ACT examination panel reports test scores ranging from 1-36 for each of the following: Composite, Mathematics, Reading, English and Science.

[58] This regression is not a Propensity Score Matching analytic and is included for reference purposes only. It is not intended to infer causality of any kind.

are the result of exams administered in the 11th grade while students who participate in DCE tend to participate starting in the 10th grade and most of Utah's ECHS students began participation in the 11th grade. For each type of dual-credit enrollment program the full treatment application may not be experienced until the end of the students' 12th grade. As such, the students have only been exposed to the treatments for a limited number of months and the students have only experienced partial effects of the treatment. Separate OLS regressions were performed and confirm statistically significant and positive relationships between the pretreatment variable and ACT scores, as well as ACT scores and the outcome variables. That the ACT score PSM estimations are nominal serves to confirm the causality of treatments on the outcomes, rather than being conditioned on the endowments of the study participants.

Of the 20 PSM analytics prepared for the panel of ACT scoring outcomes, including Composite, Math, Reading, English and Science, 14 estimations were statistically significant. They report that DCE and ECHS, both separately and jointly, have only a nominally positive ATET with a high effect of 1.348 points for the ACT Math score for the 2008 cohort for those participating in ECHS. While there were four negative outcomes, each for Reading, none was statistically significant.

## Postsecondary Higher Education Enrollment and Graduation Measurements

The measurements of DCE and ECHS in respect to postsecondary higher education enrollment and higher education graduation include measures for inside and outside of Utah higher education. Postsecondary higher education enrollment is measured rather than measuring higher education enrollment generally as dual-credit enrollees experience higher education enrollment while in high school. Further, postsecondary higher education in Utah public education is measured separately from postsecondary higher education generally in an effort to determine the effects of the treatment with respect to Utah higher education system and its outcomes as well as the treatment outcomes more generally. Higher education graduation is likewise separated into Utah higher education specific outcomes and higher education graduation outcomes generally by measuring the ATET in respect to any higher education graduation, irrespective of degree attainment for students in the target high school graduation cohorts (degree attainment is measured in Degree Attainment and Time-to-Completion section of this chapter). The estimations for these outcomes include DCE, ECHS, and combined dual credit enrollment (General) treatments, each of which are estimated for the high school graduation cohorts of 2008 and 2009 separately and in the aggregate.

*Postsecondary Higher Education Enrollment - Utah* (Figure 5.5[59]) only includes Utah higher education enrollments by students in the targeted high school graduation cohort. The estimations were all statistically significant below the 1% and were consistently positive, with coefficients ranging from 0.268 to 0.392. We see that the ATET for both DCE and ECHS, individually and in the aggregate, provides an increased probability of postsecondary higher education enrollment of between 26.8% and 39.2%. There is a substantial difference in the effects of the differentiated treatments as the

[59] Figure 5.5: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

highest treatment effect for Dual-Credit Enrollees (0.288 for the 2008 cohort) is less than the smallest treatment effect for ECHS students (0.327 for the 2009 cohort). Though both offer positive changes in the probability of a student's postsecondary higher education enrollment, ECHS participation increases the probability of postsecondary higher education enrollment by 22.1% over DCE.[60] These results were generally expected given ECHS's aim of easing the transition between high school and higher education. It likely also speaks to an investment effect as ECHS students accumulate more higher education credits than do Dual-Credit Enrollees.

*Postsecondary Higher Education Enrollment – All* (Figure 5.6[61]) includes all higher education enrollments by students in the targeted high school graduation cohort made possible by the inclusion of the National Student Clearinghouse data (NSC). The estimations were all statistically significant below the 1% and were consistently positive with coefficients ranging from 0.223 to 0.310. We see that the ATET for both DCE and ECHS, individually and in the aggregate, provides an increased probability of postsecondary higher education enrollment of between 22.31% and 31%.

There is a substantial difference in the effects of the differentiated treatments effects as the highest treatment effect for Dual-Credit Enrollees (.253 for the 2008 cohort) is less than the smallest treatment effect for ECHS students (.268 for the 2009 cohort). Though both offer positive changes in the probability of a student's postsecondary higher education enrollment, ECHS participation increases the

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[60] This percentage change was derived by averaging the effects for each of the treatments and then applying the percentage change formula: $\frac{ECHS-DCE}{DCE}(100) = \frac{0.339-0.278}{0.278}(100) = 22.1\%$

[61] Figure 5.6: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

probability of postsecondary higher education enrollment by 21.4% over DCE.[62] Again, these results were generally expected and are only nominally different from the results observed in respect to Utah higher education.

What was not necessarily expected is the difference in probabilities between postsecondary higher education enrollments for Utah higher education as compared to all higher education. The average probability of Dual-Credit Enrollees attending Utah higher education reported with an increase of 16.8%[63] as compared to the probability of attending higher education in general with an even greater increase (24.2%[64]) observed for ECS participants. Critics of these programs suggest participants are more likely to attend high profile and private higher education than public institutions owing both to the attractiveness of program graduates to these institutions and the institution's attraction to students. Though not specifically examined, the results suggest public higher education is a more attractive alternative to DCE and ECHS participants, potentially due to the investment treatment participants have in accumulated credits in Utah higher education, which credits may suffer reductions upon transfer to out-of-state and private institutions. Additionally, the existence of Utah's New Century Scholarship (Bracco & Martinez, 2005; Kearl, 2012) may also be a determinant in this relation. Utah public education students earning an Associate's Degree coincident with

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[62] This percentage change was derived by averaging the effects for each of the treatments and then applying the percentage change formula: $\frac{ECHS-DCE}{DCE}(100) = \frac{0.289-0.238}{0.238}(100) = 21.4.7\%$

[63] This percentage change was derived by averaging the effects for each of the treatments and then applying the percentage change formula: $\frac{DCE(UT)-DCE(ALL)}{DCE\ (ALL)}(100) = \frac{0..278-0.238}{0.238}(100) = 16.8\%.$

[64] This percentage change was derived by averaging the effects for each of the treatments and then applying the percentage change formula: $\frac{ECHS(UT)-ECHS(ALL)}{ECHS\ (ALL)}(100) = \frac{0.359-0.289}{0.289}(100) = 24.2\%.$

receiving their high school diplomas may qualify for scholarship funding to pay for as much as 75% of their remaining higher education tuition expense at any Utah higher education institution.[65]

*Higher Education Graduation – Utah* (Figure 5.7[66]): The data for *Higher Education Graduation - Utah* in this study include all higher education graduations from institutions associated with the Utah System of Higher Education (USHE), including various certificate, Associate, Bachelor and graduate degrees, and reports as a binary variable, regardless of the number of graduations any particular student may have. The analysis is exclusive to graduations from Utah higher education and does not include higher education graduations, public or private, outside of those institutions overseen by USHE. The estimates are reflective of the ATET for Utah higher education graduation of those students from the Utah public high school graduation cohorts of 2008 and 2009 who enrolled in Utah higher education after the completion of high school and do not include data on those who did not enroll.

Each of the four estimations for higher education graduation is statistically significant below the 1%. The coefficients are consistently positive and range from 0.084 to .429. We see that the ATET for both DCE and ECHS, individually and in the aggregate, reflect an increased the probability of higher education graduation of between 8.4% and 42.9% when compared to those who did not participate in the treatment. There is a substantial difference in the effects of the differentiated

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[65] The New Century Scholarship award levels and school applicability experienced changes during the targeted cohort years and may affect different cohort year students differently.

[66] Figure 5.7: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

treatments with largest effect of DCE (0.084) being substantially less than the smallest effect of ECHS (0.402).

Of interest in this outcome panel is the difference in ATET based on the applied treatment. ECHS participation results in an increase in Utah higher education graduation of 40.2% and 42.9% for the 2008 and 2009 high school graduation cohorts, respectively, as compared to the ATET for DCE 8.4% and 59%. A substantial portion of this difference is the result of the high level of ECHS participants earning an Associate's Degree coincident with their high school graduations.

*Higher Education Graduation – All* (Figure 5.8[67]): The data for *Higher Education Graduation – All* in this study include all higher education graduations from all higher education institutions regardless of the state in which the institution is located or its public/private nature. The examination includes various certificate, Associate, Bachelor's and graduate degrees, and reports as a binary variable, regardless of the number of graduations any particular student may have. As expected, the estimation coefficients are statistically significant and consistently positive.

Each of the nine estimations for higher education graduation is statistically significant below the 1%. The coefficients are consistently positive and range from 0.147 to .441. We see that the ATET for both DCE and ECHS, individually and in the aggregate, increases the probability of higher education graduation of between 14.7% and 44.1% when compared to those who did not participate in the treatment. There is a substantial difference in the effects of the differentiated treatments with the largest

[67] Figure 5.8: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

effect of DCE (0.223) being substantially less than the smallest effect of ECHS (0.36). ECHS participation results in an increase in Utah higher education graduation of 36% and 44.1% for the 2008 and 2009 high school graduation cohorts, respectively, as compared to the ATET for DCE 14.7% and 22.3%, respectively. A substantial portion of this difference is the result of the high level of ECHS participants earning an Associate's Degree coincident with their high school graduations.

## Degree Attainment and Time-to-Completion

In respect to degree attainment, the outcome variables (Highest Higher Education Degree: Associate's, Bachelor's, and Masters) are measured against the treatments (DCE and ECHS, separately and collectively) for which both the outcome and treatment variables are binary. The estimations for Time-to-Completion (Associate's and Bachelor's) are similarly analyzed though with continuous outcomes. As such the reported coefficients are measures of the number of days between after high school graduation and degree specific higher education graduation.

*Time-to-Completion* (Figures 5.9[68] and 5.10[69]): This examination offers an estimation of the effects of DCE and/or ECHS on higher education time-to-completion (Associate's and Bachelor's) for those students from the Utah public high school graduation cohorts of 2008 and 2009 who enrolled in, and subsequently graduated from, Utah higher education, specifically from those institutions overseen by the Utah

[68] Figure 5.9: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[69] Figure 5.10: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

System of Higher Education. Time-to-Completion for a Master's is not estimated due to the low number of these degrees earned by students in the targeted cohorts. In this case, time-to-completion is the number of days between public high school graduation and graduation from Utah higher education; is exclusive to degree attainment through Utah higher education, and does not include higher education degree attainment, public or private, outside of those institutions overseen by the USHE. It is reported as a negative value and gauges the temporal benefit obtained as a result of participating in the target treatments.

*Associate's Degree*: Each of the nine estimations is statistically significant below the 1% and the coefficients are consistently negative and range from -851.66 and -262.3. This outcome variable is temporal and continuous and as such, the coefficients represent changes in numbers of days for the treated population (shown as positive change in days-to-completion in Figure 5.9). We see that the ATET for both DCE and ECHS, individually and in the aggregate, provides a negative effect on the number of days between high school and higher education graduation with an Associate's Degree is between 262.3 and 851.66 days when compared to those who did not participate in treatment. There is a substantial and expected difference in the effects of the differentiated treatments with the largest effect of DCE (-266.12) being 571.67 days less than the smallest effect of ECHS (-837.79). This effect is, in part, a reflection of the structure and goal of the ECHS treatment as its participants are provided a pathway towards earning an Associate's Degree coincident with high school graduation. Such an advantage would result in a decrease in time-to-completion of as many as 730 days, all else being equal.

*Bachelor's Degree*: Each of the four estimations is statistically significant below the 1% and provides a negative correlation between treatment participation and time-to-completion; treatment participation results in fewer days to Bachelor's Degree completion. We see that the ATET for both DCE and ECHS, individually and in the aggregate, provides a negative effect on the number of days between high school and higher education graduation with a Bachelor's Degree is between -167.04 and –316.94. As would be expected, there is a substantial difference in the effects of the differentiated treatments. The coefficients for the DCE treatment being -167.04 and -188.94 for the 2008 and 2009 high school graduation cohorts, respectively, while the ECHS treatment is -249.17 and -316.94. This effect may, in part, be a reflection of course availability and course requirements for any given major in Utah higher education. It may also be reflective of a potential lack of preparation high school students may experience in selecting a higher education major and then selecting dual-credit enrollment courses to be applied to that major 2 or more years in their futures.

*Higher Education Degree Attainment - USHE* (Figures 5.11[70] and 5.12[71]): This examination offers an estimation of the effects of DCE and/or ECHS (treatments) on the highest higher education degree attained (Associate's or Bachelor's) by students in Utah public high school graduation cohorts of 2008 and 2009 who enrolled in, and

[70] Figure 5.11: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[71] Figure 5.12: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

subsequently graduated from, the Utah System of Higher Education. There were fewer than 10 Master's Degrees earned by cohort members as of the date the subject data was collected, and as such, PSM estimates were not calculated for this outcome.

*Associate's Degree*: Each of the four estimations is statistically significant below the 1% and is consistently positive with coefficients ranging from 0.105 to 0.173. We see that the ATET for both DCE and ECHS, individually and in the aggregate, provides a positive effect on the probability of an Associate's Degree being the highest higher education degree attained by a student from the subject Utah high school graduation cohorts is between 10.5% and 17.3% when compared to those who did not participate in treatment. There is not a substantial difference in the effects of the differentiated treatments with the coefficient range for DCE of .105 to 0.15 being only nominally different from that of ECHS (0.138 and 0.178).

*Bachelor's Degree*: None of the four estimations for highest Higher Education Degree – USHE is statistically significant at any plausible level, with the remaining, though the estimates are backed up by ROC curves with areas under the curve of 0.76, indicating a satisfactory degree of model accuracy. The PSM estimates range from a low of 0.020 and 0.048 indicating an increase in probability of students remaining in the USHE system of earning a Bachelor's Degree of between 2% and 4.8% when compared to those who did not participate in either of the treatments.

*Higher Education Degree Attained – All* (Figure 5.13[72]): This examination offers an estimation of the effects of DCE and/or ECHS (treatments) on the highest higher

[72] Figure 5.13: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

education degree attained (Associate's or Bachelor's) by students in Utah public high school graduation cohorts of 2008 and 2009 who enrolled in, and subsequently graduated from, any institution of higher education. There were fewer than 10 Master's Degrees earned by cohort members as of the date the subject data were collected, and as such, PSM estimates were not calculated.

*Associate's Degree*: Each of the four estimations is statistically significant below the 10% level. The coefficients are consistently positive and range from 0.068 to 0.245. We see that the ATET for both DCE and ECHS, individually and in the aggregate, provides a positive effect on the probability of an Associate's Degree being the highest higher education degree attained by a student from the Utah high school graduation target cohorts is between 6.8% and 24.5% when compared to those who did not participate in treatment. There is not a substantial difference in the effects of the differentiated treatments though the coefficient range for DCE of .082 and 0.127 is lower than that for ECHS students of 0.131 and 0.137 for 2008 and 2009, respectively.

*Bachelor's Degree*: None of the four estimates for *Higher Education Degree: Bachelor's – All* is statistically significant at any plausible level, though the estimations represent a change in the probability of those students participating in DCE or ECHS of between -0.01 and 0.11.

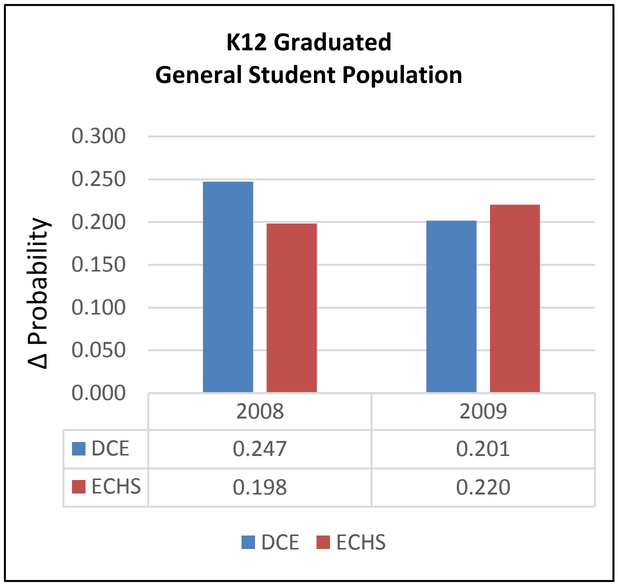



**Figure 5.1 K12 Graduated: General Student Population**

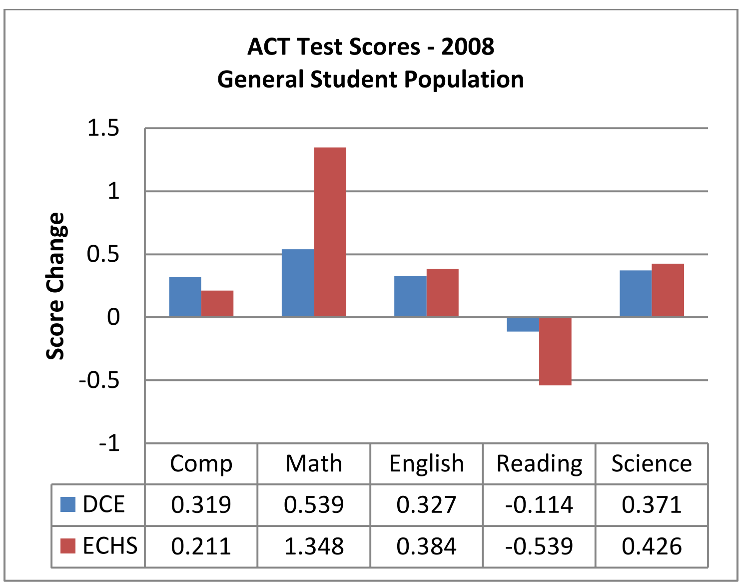
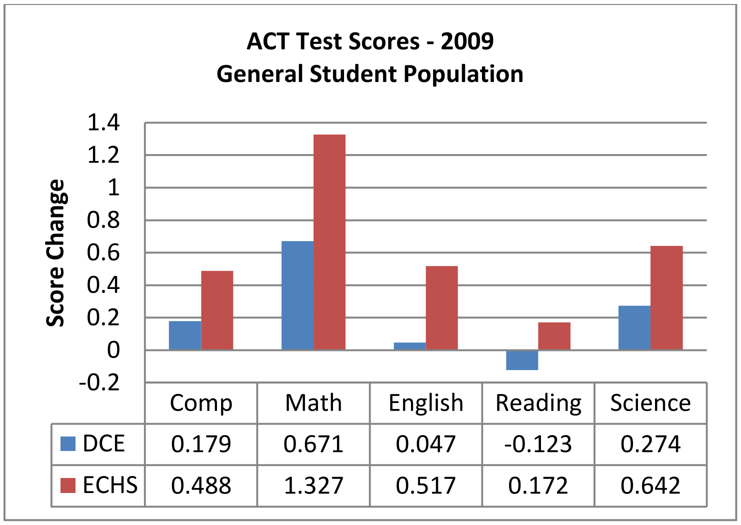
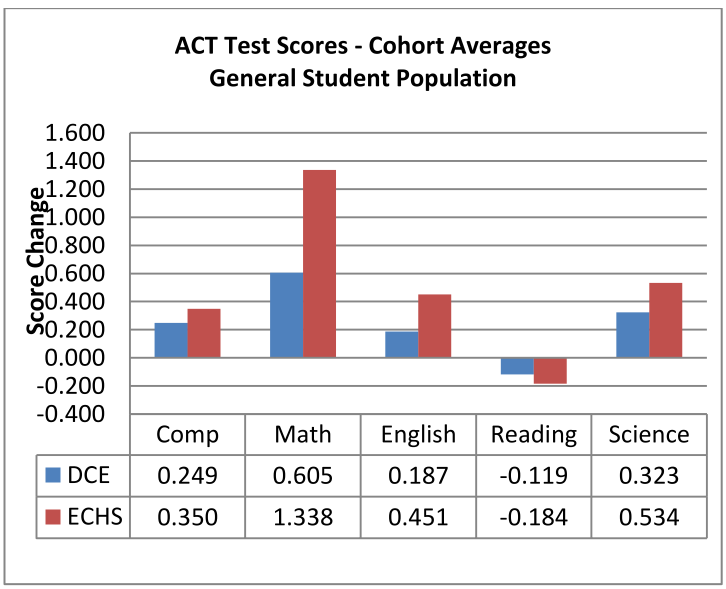



**Figure 5.2 ACT Test Scores – 2008: General Student Population**




| | Comp | Math | English | Reading | Science |
|---|---|---|---|---|---|
| DCE | 0.179 | 0.671 | 0.047 | -0.123 | 0.274 |
| ECHS | 0.488 | 1.327 | 0.517 | 0.172 | 0.642 |

**Figure 5.3 ACT Test Scores – 2009: General Student Population**




| | Comp | Math | English | Reading | Science |
|---|---|---|---|---|---|
| DCE | 0.249 | 0.605 | 0.187 | -0.119 | 0.323 |
| ECHS | 0.350 | 1.338 | 0.451 | -0.184 | 0.534 |

**Figure 5.4 ACT Test Scores – Cohort Averages: General Student Population**

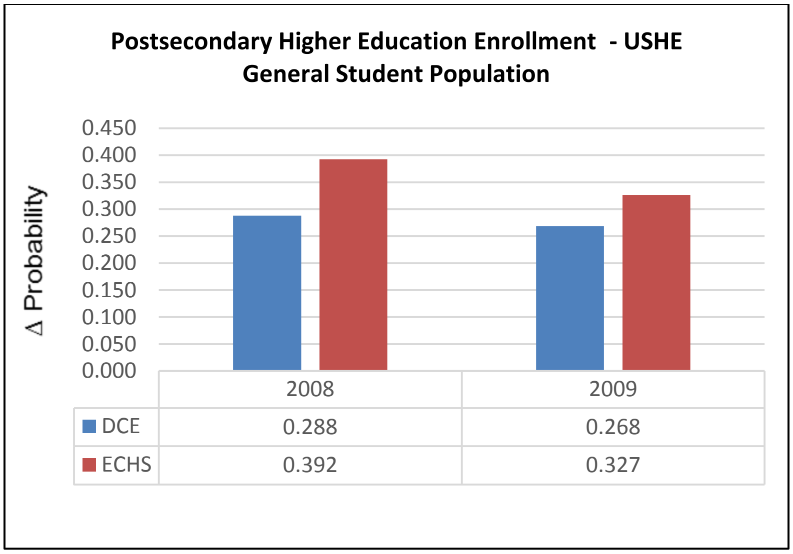



**Figure 5.5 Postsecondary Higher Education Enrollment - USHE**

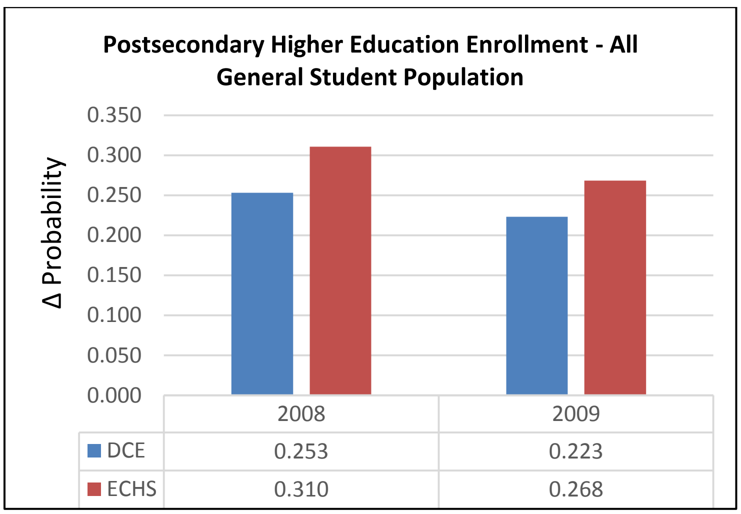



**Figure 5.6 Postsecondary Higher Education Enrollment - All**

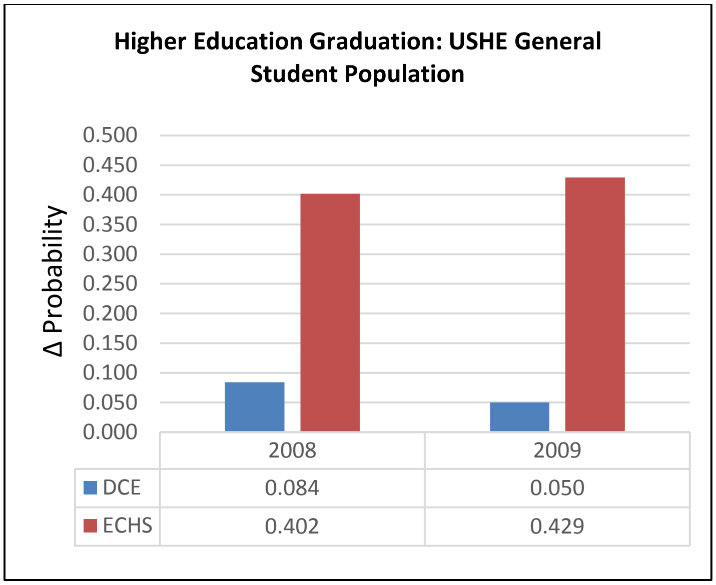



**Figure 5.7 Higher Education Graduation - USHE**

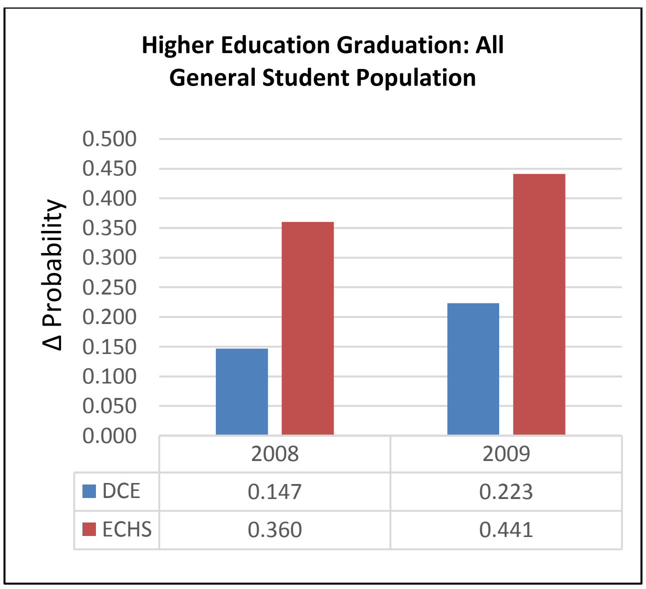



**Figure 5.8 Higher Education Graduation - All**

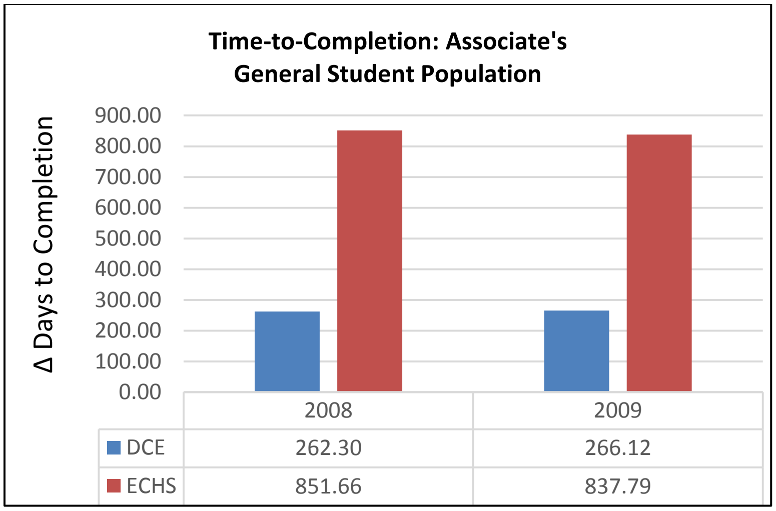



**Figure 5.9 Time-to-Completion – Associate's: General Student Population**

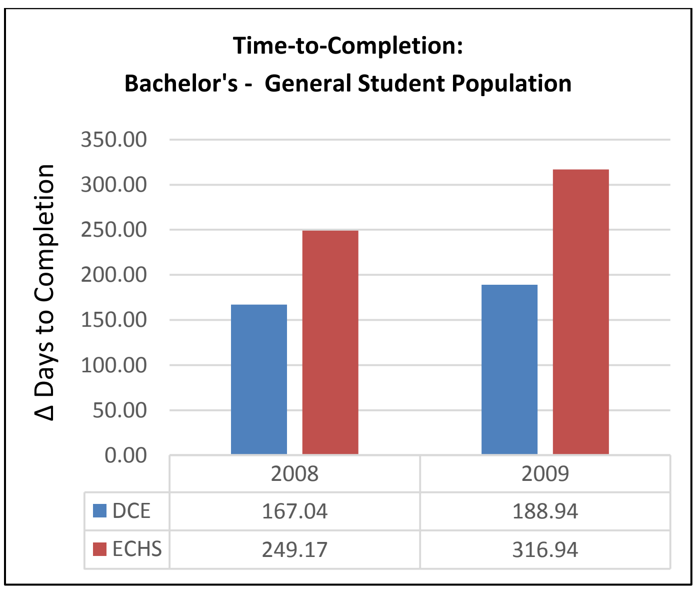



**Figure 5.10 Time-to-Completion – Bachelor's: General Student Population**

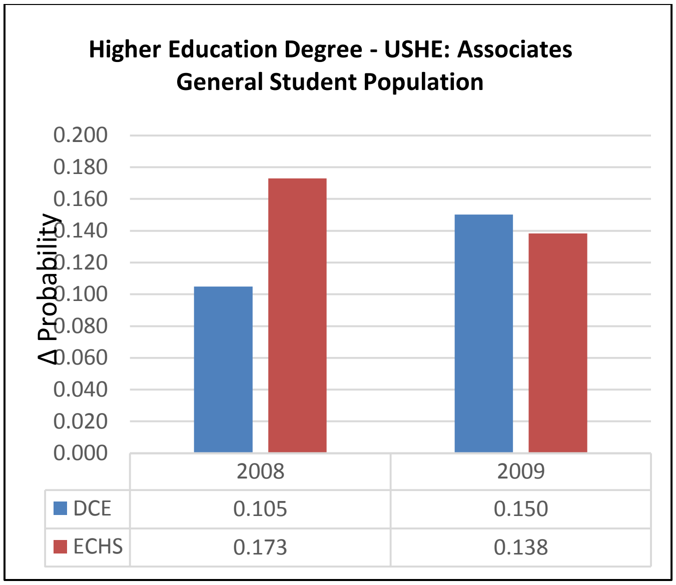



**Figure 5. 11 Higher Education Degree – USHE: General Student Population**

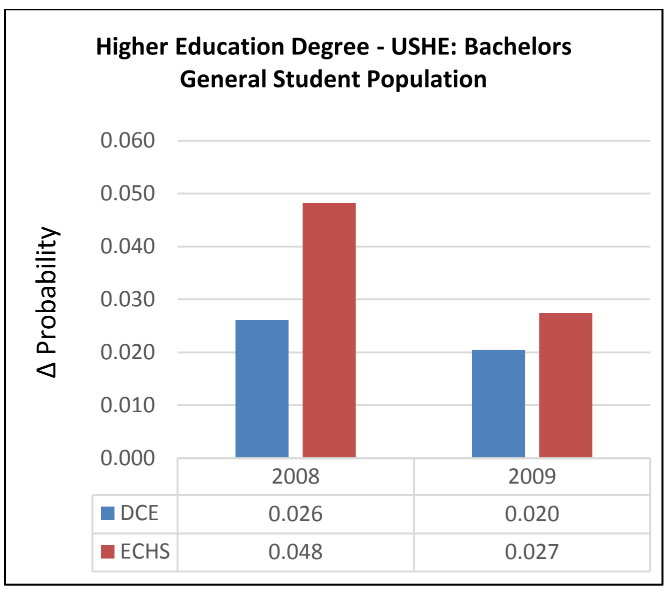



**Figure 5.12 Higher Education Degree – USHE: General Student Population**

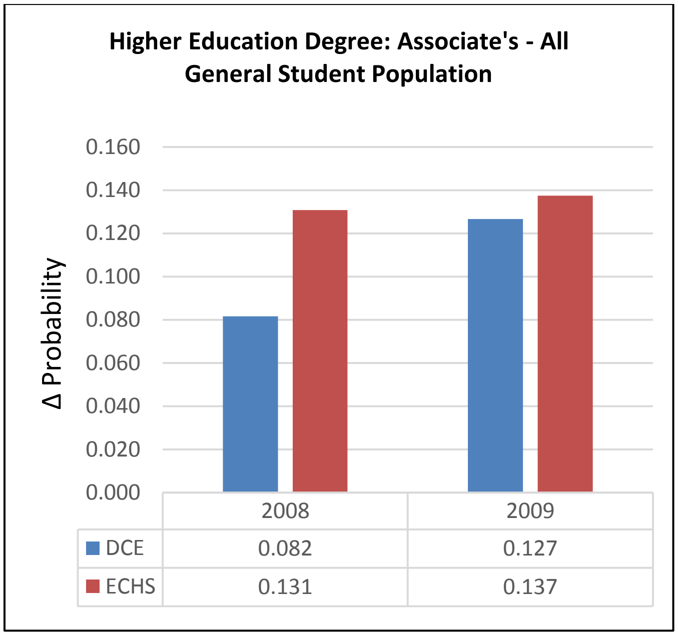



**Figure 5.13 Higher Education Degree: Associate’s – All: General Student Population**

# 6. UNDERREPRESENTED STUDENT POPULATION RESULTS

Dual-Credit Enrollment (DCE) and Early College High School (ECHS) programs, as supported by state legislatures and both state and national level departments of education, are to be targeted to underrepresented populations in an effort to improve economic and social productivity of these populations and to decrease the growing income gaps between various socio-economic groups. In this section, we consider the secondary and higher education outcomes of a variety of demographic subgroups differentiated by treatment but also compare the outcomes of treated members of a subgroup and those of the general student population. The examined outcomes are the same as those considered for the for the general student population with respect to higher education, but the only high school level outcomes examined are high school graduation and ACT Composite scores; scores for Math, Reading, English and Science are not expressly examined for underrepresented students. In the case of DCE, the control group is those students who did not participate in any form of dual credit enrollment, and the control group for considering of ECHS is also those who did not participate in any form of dual-credit enrollment.

Unlike the general student population examination, the reported outcomes for the 2008 and 2009 high school graduation cohorts are averaged, though each individual cohort's results are available in Appendix E through M, including coefficients, standard errors, *z* scores, *p* values and 95% confidence intervals for each outcome measured for each cohort, student subgroup, and treatment combination based on PSM average treatment effects of the treated. Appendix C reports the Receiver Operating Characteristic analysis similarly and offers area under the curve results for each outcome, student subgroup, and treatment combination. The following discussion includes the Propensity Score Matching estimation coefficients for many of the estimated outcomes in this study and only specifies a model's ROC area under the curve (AUC) in the event the PSM analytic lacks statistical significance ($P>|z|$ exceeding .10).[73]

The differentiated subgroups include female, male, minority, low income, English language learner, minority male, minority female, low income male and low income female student populations. Including males as a subgroup amongst underrepresented students may be counter intuitive, but as the data show, males are "underrepresented" in higher education compared to females generally. They also fare poorly compared to females in many of the measured outcomes and the treatment effects for this subgroup are often higher than for other subgroups. As such, both males and females are included as underrepresented students in this analysis.

Both DCE and ECHS program participant (treatments) reflect improved high school graduation experience compared to traditional (TRAD), but there is limited difference in the outcomes of the two programs. General population student treatment

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[73] Of the 144 ROC estimations performed against the Underrepresented Student Population PSM models, only one indicated a weak model; that particular model considered the Early College High School's effect on an English Language learner's probability of earning an Associate's Degree through Utah public higher education. Of 170 PSM estimations with respect to underrepresented students, 26.5% (45) estimations experienced problems with statistical significance such that they were not found to be significant at any plausible level.

participation reflects improved probability of K12 graduation of 20.9% and 22.4%, respectively. While each of the subgroups reflects yet greater improvements, low income and minority males show the greatest improvement, 32.8% and 36.7% for minority males and 30.9% and 35.5% for low income males. The graduation experience of low income females is also much improved, but by a lesser margin, 29.1% and 30.4% (Figure 6.1[74]).

While DCE and ECHS effects on ACT scores for Math, Reading, English, and Science were estimated and reported for underrepresented students, only ACT Composite scores are included in this section. While the average treatment effect on the treated is marginal for the general student population with point changes of .249 and .35, respectively, (out of a total possible score of 36), males, minority students, and low income males and females received the strongest score improvements among the subgroups. Even then, the score increases were marginal and no examined subgroup reflect score increases of one point or greater. Though fully one half of the 40 PSM estimates for this outcome experienced problems with statistical significance, the lowest ROC AUC for those problematic estimates was 0.616 (ECHS Female) and all other AUCs were between 0.729 and 0.827.

Postsecondary higher education enrollment in Utah public higher education (USHE) is of particular import to this study and the PSM estimates show that improved probabilities of attending enrolling in Utah higher education of between 26.5% and

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[74] Figure 6.1: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

34.5% for DCE participants and 30.2% and 40.1% for ECHS students (Figure 6.2[75]). This compares to 27.8% and 36% for general population students and differs only slightly when the analysis extends to all postsecondary higher education enrollments (Figure 6.3[76]).

Higher education graduation includes the earning of an Associate's Degree or higher in this study. Utah Higher Education graduation outcomes reflective of DCE treatment participation was relatively low for the general student population in each of the subgroups, with probability of higher education graduation improvements in the USHE system ranging from 2.2% for minority males to 7.5% for females; with an improvement of 6.7% for the general student population.

ECHS participants present an entirely different picture with the lowest probability improvement within minority females at 16.7% and the highest improvement amongst males of 44.7%; the general student population was 41.5%. As for postsecondary higher education outcomes, there was little difference between improved graduation experience within Utah public higher education (Figure 6.4[77]) and higher education generally (Figure 6.5[78]). The structure of ECHS programs in Utah accounts for much of the probability improvement as ECHS participants accumulate significantly higher education credits, leading to Associate's Degree attainment rates of as high as 72% amongst Utah's six Early College High Schools.

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[75] Figure 6.2: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[76] Figure 6.3: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[77] Figure 6.4: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[78] Figure 6.5: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

Higher education time-to-completion in this study examines Associate's and Bachelor's Degrees earned through all of higher education. The reported coefficients are the decrease in number of days-to-completion resulting for DCE and ECHS participation. While these are reflected as positive values in the presented figures (Figure 6.6[79] and 6.7[80]) they are reported as negative values in the PSM outcomes**.**

Amongst DCE participants who earned an Associate's Degree during the study period, males generally and low income males experienced the greatest improvements of 328 and 276 fewer days to completion, but even the lowest levels of improvement, found in minority males, reflect improvements of more than 194 days. ECHS participants experienced significantly greater gains, once again owing to program structure, as males and low income males experienced improvements of 993 and 992 days, respectively. The lowest level of improvement for ECHS participants was found among low income females at 675 days. The only problem with statistical significance among these estimates was found for minority females, for which the ROC AUC is 0.9, reflecting a highly accurate model for this estimation.

While higher education time-to-completion for those earning Bachelor's Degrees reflects improvements for each subgroup, there are a few significance problems that correlate with low ROC AUC values. There were sufficiently few English language learners amongst ECHS participants that an AUC could not be calculated and statistical significance is below any plausible level. The AUC for minority females was only 0.5371,

[79] Figure 6.6: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

[80] Figure 6.7: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

a level just barely above that which might be obtained via random guessing. As such, while the outcomes for these groups are reported, they are not reliable.   Amongst those with reliable outcomes, minority students and low income females had the greatest gains of 419 and 446 days, respectively, well above the gains of the general student population.  Also of interest is a comparison of the gains experienced for those earning and Associate's Degree and a Bachelor's Degree.  Much of the gains for Associate's Degree earners dissipate when it comes to earning a Bachelor's Degree; as noted, this is discussed in greater detail in Chapter 7.

PSM estimates for higher education graduation for Associate's Degrees reflect (Figure 6.8[81]) the greatest improvement in probability of degree attainment among minority males and minority females.  DCE participants experienced improvements of 10.6% and 8.5%, respectively, while ECHS participants saw gains of 18.3% and 19%. General student population gains were 2.3% for DCE students and 4.1% for ECHS students and the gains experienced by each of the remaining subgroups exceeded those of the general student population by an average of 3.6% and 4.6% for DCE and ECHS participants, respectively.

Eight of the forty PSM estimates for this outcome experienced problems of statistical significance, though the average ROC AUC was 0.7425 with a low of 0.6459 and high of 0.8182, suggesting the models were reasonably specified and of sufficient strength to be reliable.   The PSM and ROC outcomes for Higher Education Graduation: Bachelor's suffered extensively from such levels of statistical significance that it renders

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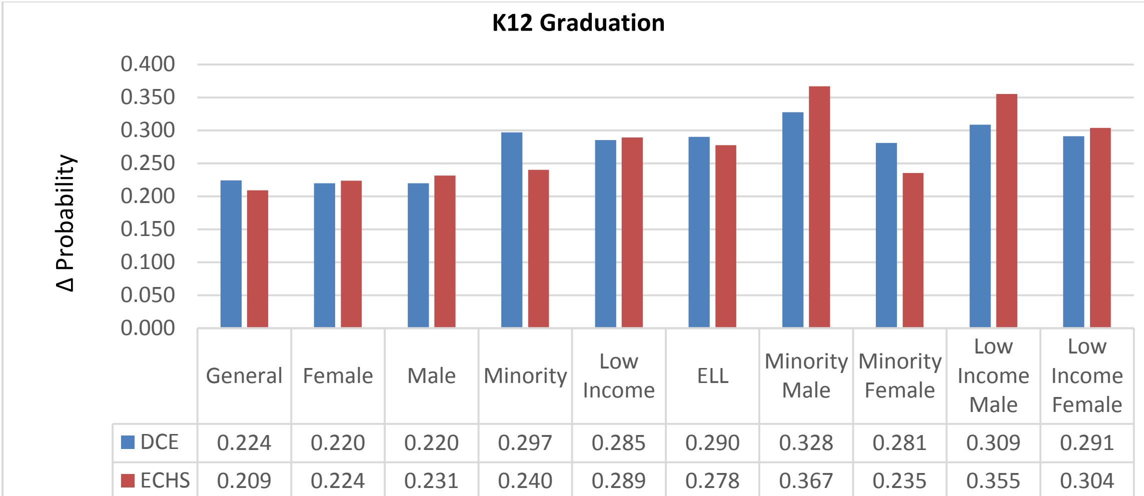
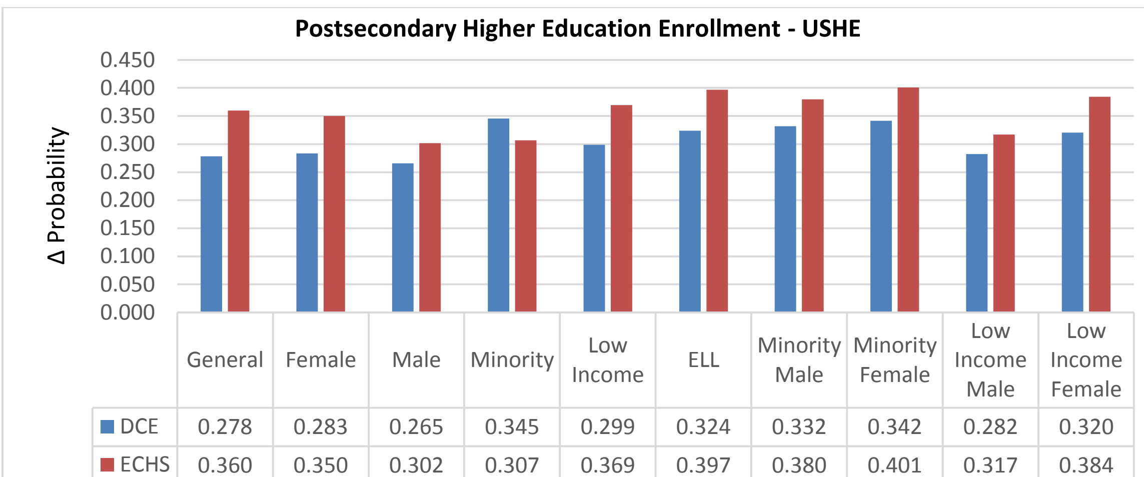
[81] Figure 6.8: Utah Data Alliance; 2008 & 2009 Public High School Graduation Cohorts, 2013 data release

reporting the outcomes irresponsible, and as such, these outcomes can be found in the outcome tables in Appendix C through M, but are not discussed here nor are they relied on for Chapter 7's policy discussion and recommendations.



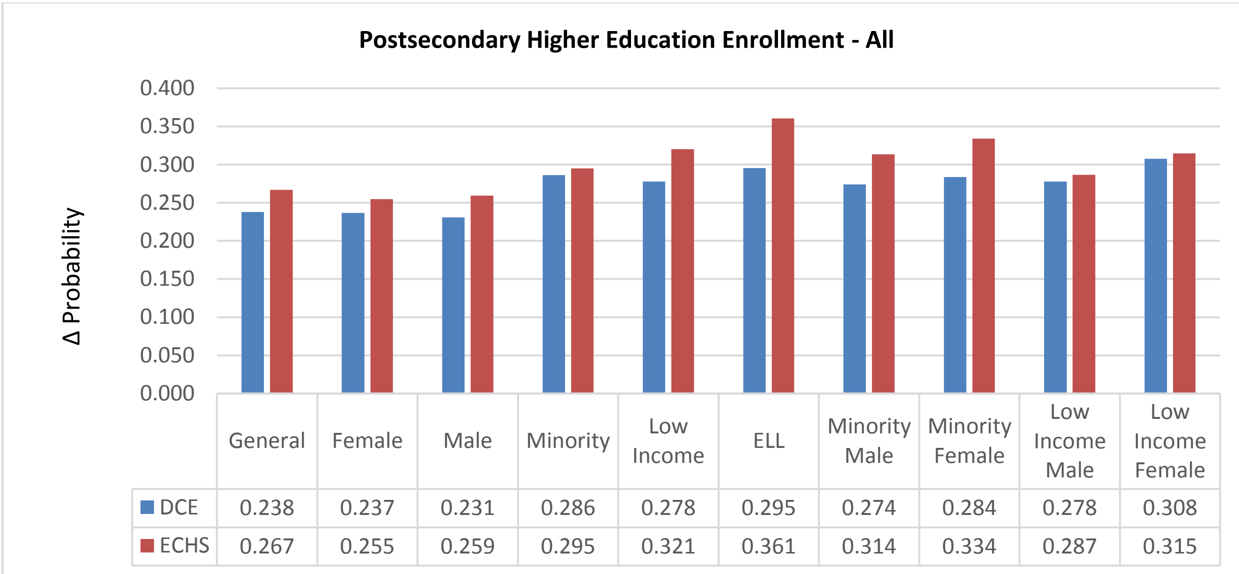

| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 0.224 | 0.220 | 0.220 | 0.297 | 0.285 | 0.290 | 0.328 | 0.281 | 0.309 | 0.291 |
| ECHS | 0.209 | 0.224 | 0.231 | 0.240 | 0.289 | 0.278 | 0.367 | 0.235 | 0.355 | 0.304 |

**Figure 6.1 K12 Graduation**



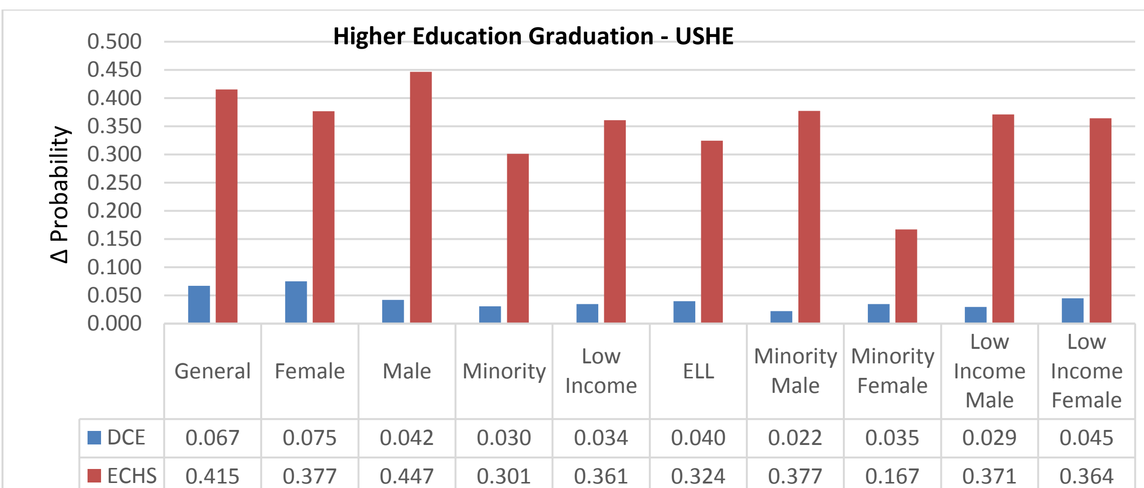

| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 0.278 | 0.283 | 0.265 | 0.345 | 0.299 | 0.324 | 0.332 | 0.342 | 0.282 | 0.320 |
| ECHS | 0.360 | 0.350 | 0.302 | 0.307 | 0.369 | 0.397 | 0.380 | 0.401 | 0.317 | 0.384 |

**Figure 6.2 Postsecondary Higher Education Enrollment - USHE**



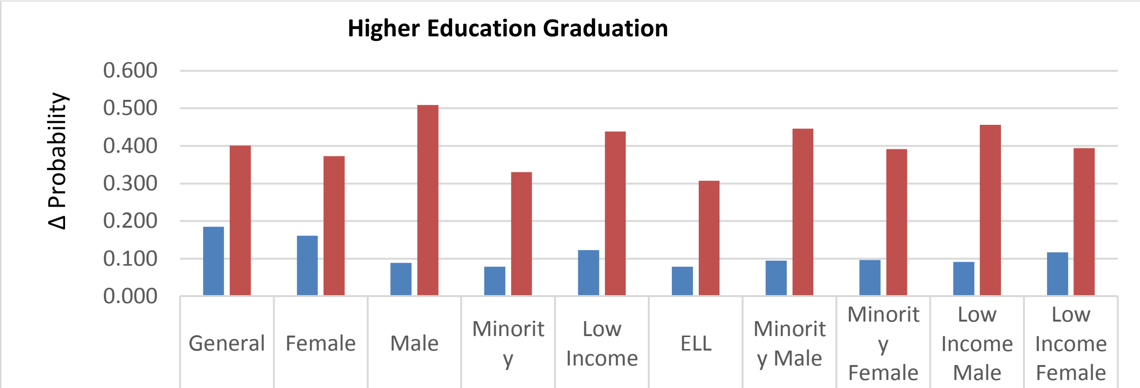

| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 0.238 | 0.237 | 0.231 | 0.286 | 0.278 | 0.295 | 0.274 | 0.284 | 0.278 | 0.308 |
| ECHS | 0.267 | 0.255 | 0.259 | 0.295 | 0.321 | 0.361 | 0.314 | 0.334 | 0.287 | 0.315 |

**Figure 6.3 Postsecondary Higher Education Enrollment - All**



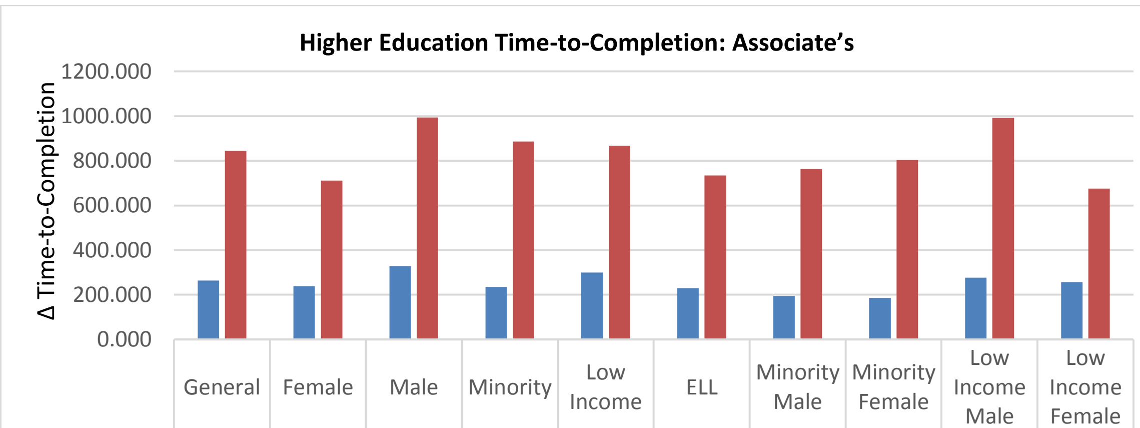

| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 0.067 | 0.075 | 0.042 | 0.030 | 0.034 | 0.040 | 0.022 | 0.035 | 0.029 | 0.045 |
| ECHS | 0.415 | 0.377 | 0.447 | 0.301 | 0.361 | 0.324 | 0.377 | 0.167 | 0.371 | 0.364 |

**Figure 6.4 Higher Education Graduation - USHE**



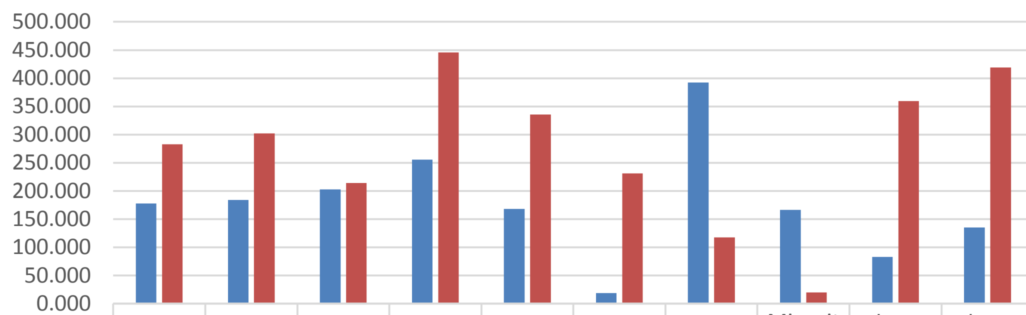

| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 0.185 | 0.161 | 0.088 | 0.078 | 0.123 | 0.078 | 0.094 | 0.096 | 0.091 | 0.116 |
| ECHS | 0.401 | 0.372 | 0.509 | 0.331 | 0.439 | 0.308 | 0.446 | 0.391 | 0.456 | 0.394 |

**Figure 6.5 Higher Education Graduation - All**



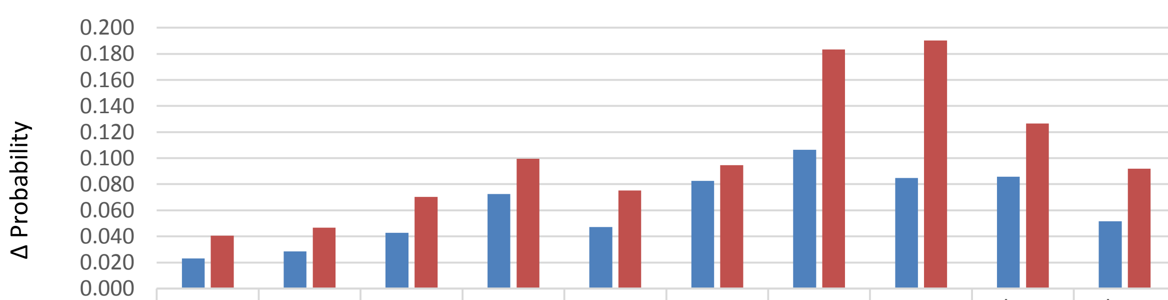

| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 264.210 | 238.083 | 328.130 | 234.949 | 299.163 | 228.870 | 194.787 | 185.927 | 276.402 | 255.939 |
| ECHS | 844.726 | 711.646 | 993.298 | 885.859 | 867.485 | 734.434 | 762.400 | 803.177 | 991.912 | 674.848 |

**Figure 6.6 Higher Education Time-to-Completion: Associate's**




| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 177.988 | 183.903 | 203.040 | 255.512 | 168.328 | 18.852 | 392.212 | 166.725 | 83.154 | 134.987 |
| ECHS | 283.055 | 302.275 | 214.107 | 445.654 | 335.552 | 230.964 | 117.500 | 19.750 | 359.500 | 419.034 |

**Figure 6.7 Higher Education Time-to-Completion: Bachelor's**




| | General | Female | Male | Minority | Low Income | ELL | Minority Male | Minority Female | Low Income Male | Low Income Female |
|---|---|---|---|---|---|---|---|---|---|---|
| DCE | 0.023 | 0.029 | 0.043 | 0.073 | 0.047 | 0.083 | 0.106 | 0.085 | 0.086 | 0.052 |
| ECHS | 0.041 | 0.047 | 0.070 | 0.100 | 0.075 | 0.095 | 0.183 | 0.190 | 0.127 | 0.092 |

**Figure 6.8 Higher Education Graduation: Associate's**

# 7. CONCLUSION, POLICY CONSIDERATIONS, AND FURTHER RESEARCH

The success and growth of dual-credit enrollment programs to date have brought them into sharp focus for policy makers, but until recently, the data to assess their objective levels of success have been limited. With the release of the Utah Education Longitudinal Data, and similar data sets like it in other states, we're only now beginning to separate the effects of Dual-Credit Enrollment from those of Early College High School with respect to high school and higher education outcomes. An analysis of labor market outcomes, which many hold as the true test of these programs, remains several years away as the first high school graduates from these differentiated programs only recently began to graduate from higher education.

Clearly, student success is a function of numerous inputs, of which formal education comprises only part, but an important part nonetheless. Influential household level attributes such as parental and sibling education, household composition, social networks and student intellect form what we might refer to as household endowments with respect to education, but these neither negate nor discount the import of education policy with respect to student success. The available Utah data largely include variables specifically related to education policy with only a limited number of demographic and socio-economic variables to aid us in considering the effects of the students' household endowments on high school and higher education outcomes. However, as we examine outcomes for underrepresented students, these variables, combined with those which measure specific outcomes are sufficiently important to render the analysis meaningful, if not perfect.

Students from an increasingly wide set of income and race backgrounds are populating the nation's high schools, colleges and universities. The male gender bias once pervasive in higher education participation, completion and degree attainment now appears to have shifted towards a decided female bias in all but select courses of study. These changes are becoming especially important to Utah policy makers, but the reality that transition from high school to higher education remains difficult for low income, minority and English language learner students is persistent. This difficulty ultimately equates to lesser rates of high school graduation, and higher education enrollment, completion and degree attainment for these populations compared to their peers and ultimately results in lower levels of productivity and income in the labor markets.

## Policy Considerations

Policy aimed at effecting household endowments is difficult to plan and execute, and often takes many years for benefits to be realized. Though it may not be immediately obvious, policy directed towards high school and higher education for a given generation results in household endowment changes in future generations. As such, public education policy that even offers marginal improvement may have long lasting and multiplicative socio-economic effects; this is especially true of those policies yielding important gains for underrepresented students.

In March 2014 the Utah Association of Public Charter School awarded Itineris Early College High School, one of the state's six Early College High Schools, as the Charter School of the Year[82] as a result of the school's success in attracting underrepresented students and preparing students for higher education. A comparison by race shows the school's racial composition (Figure 7.1[83]) virtually mirrored that of the state's public education system (USOE) and represented significant improvements over dual-credit enrollment generally (Utah CC). A comparison by gender (Figure 7.2[84]) reflects similar improvements. The school's male/female composition was similar to that of the state, with more males and fewer females, and more ethnically balanced than the state's dual-credit enrollment programs. For the academic year ending June 2013 Itineris's 241 dual-credit enrollment students earned 5,641 higher education credit hours, more than 23 units per student[85] compared to an average of 6.9 per concurrent enrollment student for the state generally, a figure that has remained relatively constant for several years. Additionally 78% of its graduating seniors earned an

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[82] Utah Association of Public Charter Schools; March 21, 2014: https://utahcharters.org/charter-schools-in-utah/the-best-of-the-best/

[83] USOE Finger Tip Facts 2013: http://www.schools.utah.gov/data/Fingertip-Facts/2013_FingertipFacts.aspx

[84] Data compiled from USOE and USHE 2012-2013 Concurrent Enrollment Summary Data, January 7, 2014, USHE Concurrent Enrollment Annual Report 2012-2013 (http://higheredutah.org/pdf/reports/ConcurrentEnrollment%20-12-13_Report.pdf) and Itineris UTREx Clearinghouse – School Summary 2012-2013.

[85] Itineris Early College High School: http://www.iechs.org/

Associate's Degree from Salt Lake Community College and were awarded $1,815,92 in scholarships. The school's experience evidences the success of dual credit enrollment does not have to come at the cost of diversity and inclusion.

This study has shown that dual-credit enrollment programs yield varying levels of improvements in the probability of female, male minority, low income, and English language learner students high school graduation, postsecondary higher education enrollment, and higher education graduation and degree attainment. These positive correlations suggest that these programs, when analyzed as treatments on student populations, aid in improving the student condition and preparing students for their next steps into society and the markets. Where Dual-Credit Enrollment and Early College High School improve underrepresented students' probability of high school graduation by an average of 27.4% and improve postsecondary higher education enrollment by 30.7% and 35.7%, respectively, they set the stage for improved rates of higher education completion and degree attainment. Dual-Credit Enrollment's relationship between program participation and Utah public higher education graduation averaged 4.5% for the targeted high school graduation cohorts and while this may seem to be a small marginal effect, the impact on the 90,542 student in these cohorts could result in nearly 4,100 additional higher education degree holders in the state. Similar measures for Early College High School students, with gains in the probability of Utah public higher education graduation of 35%, may yield multiples of that value.

However, not all students are interested in participating in dual-credit enrollment programs, and were any given state to attempt to include all high school students in either of these programs the effective gains would certainly diminish. But for those who do participate, the gains may yield life changing benefits.

While it may be difficult to measure the particular economic effects of most of the outcomes measured in this study, the economics of providing higher education credit hours during high school versus while enrolled in higher education is relatively straight forward, as may be the temporal benefit resulting from the decreased time-to-completion due to dual-credit enrollment programs.

During the academic year 2009-2010, the State of Utah allocated $6,165,271 for Advanced Placement and Concurrent Enrollment programs at the public high school level, resulting in 194,614 higher education credits earned by 28,185 students, an average of 6.9 credit hours for each participating student at a cost of $218.74 per student or $31.70 per credit hour. Had these students enrolled in the same number of credit hours at Salt Lake Community College during the same year, the per unit cost based on a full-time-equivalence of 14 credit hours at a cost of $2,416 per semester (USHE Data Book 2011) would have resulted in a combined cost to the state and household of $172.57. The net effect of these students having the opportunity to earn higher education credit hours under dual-credit enrollment programs resulted in a combined state and household level cost savings of $140.87 per credit hour for a total of

$27,415,274.18.[86] Of this amount, households would have borne $19,391,895[87] in tuition expenses and the state would have borne an additional $8,023,935[88] over and above that which had already been spent on these same students and credit hours at the high school level.

Low income and minority households, with fewer economic resources to expend on higher education, stand to experience greater gains from these savings than their better resourced counterparts. Concern over rising levels of student loan debt has increased in recent years as the household higher education costs have risen. As race and gender based income and wealth disparities remain persistent, the effects of such debt may be particularly troublesome with respect to these student populations. Decreases in household level higher education costs under dual-credit enrollment programs potentially reduces student loan debt levels giving rise to longer-term benefits as household discretionary income increases due to lower levels of debt servicing. These affordability effects may be contributing factors to the improved probabilities

[86] Calculation of total cost savings: Based on a per academic year FTE at 14 credit hours and two semesters per year, the per year total cost of lower division education at Salt Lake Community College for 2009-2010 equates to $4,832 or $2,416 per semester; $172.57 per credit hour. Given the $31.70 cost per credit hour to USOE, this results in a cost savings of $140.87 per credit hour and totals $27,415,274.18 when multiplied my 194,164 credit hours.

[87] Calculation of household level savings: Based on per semester full time tuition and fees at Salt Lake Community College for academic year 2009-2010 of $1,395 and 14 credit hours per semester, the per credit hours cost equals $99.64. Multiplied by 194,614 credit hours, this equals $19,391,895.

[88] Calculation of state level savings: Based on the calculated cost savings of $140.87 per credit less the household contribution of $99.64 per credit, the state's additional cost of supporting these students as Salt Lake Community College students during the 2009-2010 academic year, over and above that which the state already contributed through supporting the cost of these students and credit hours at the high school level, equates to $41.23. Multiplied over 194,614 units, the state savings equates to $8,023,935.22.

these subgroups experience with respect to postsecondary higher education enrollment and higher education completion and degree attainment.

The benefits of reduced time-to-completion arising from dual-credit enrollment programs potentially include increased rates of labor force participation as students benefiting from these programs stand to enter the workforce at younger ages and with greater probability of increased levels of higher education completion and degree attainment. This may be especially impactful for minority students, earning Bachelor's Degrees with decreased time-to-completion of 255 and 445 days for Dual-Credit Enrollment and Early College High School, respectively; for low income students, temporal savings are along the lines of 168 and 654 days. The present and future value of these improvements are a function of employment rates, income levels and retirement ages of course, and as such may be difficult to quantify at the beginning of a student's career. However, the gains may offer important economy wide contributions through increased levels of household demand, local, state and federal tax revenues, and potential decreases in social support often required by underrepresented households.

The gains dual-credit enrollment participants experience in time-to-completion at the Associate's Degree level appear to dissipate for those students earning Bachelor's Degrees. From 299 and 867 days of improved time-to-completion for an Associate's Degree, low income student experience reflects declines of 131 and 213 days for Dual-Credit Enrollment and Early College High School, respectively. For those students who earn their Associate's Degrees, a transfer degree in General Studies is the most commonly earned. These students tend to be 17-18 years of age and have little exposure to subject areas in which they may ultimately choose to major or plan a career, and as such the major selection for a 4-year degree often includes falling back and taking courses that might have been taken in years 1 or 2 of their higher education experience or making course corrections during their 3rd and 4th years. Depending on the college or university the students selects to earn their Bachelor's Degree, some of these students find sufficient differences in course requirements that certain course credits do not transfer, or transfer at a lower credit rate, resulting in the need to retake courses or simply taking more courses than otherwise expected. Yet other students lack the emotional maturity or perspective necessary to make long-term education decisions or simply take time away from higher education, voluntarily spending down some of the advantage gained. In any event, much of the temporal advantage gained through dual-credit enrollment participation is lost for many of these students, effectively decreasing, though not eliminating, an important benefit of these programs.

Of particular import for Utah legislators and education policy makers is the effect dual-credit enrollment programs has on a student's choice of where to attend higher education. In Chapter 5 we saw that Dual-Credit Enrollment and Early College High School students experienced increased probabilities of enrolling in Utah public higher education averaging 27.8% and 35.9%, respectively, compared to 24.3% and 28.9% for all higher education enrollees. The differences, 3.5% and 7%, potentially indicate the importance of credit accumulation in Utah's higher education system. Where DCE students, who would be expected to accumulate fewer higher education credits than

ECHS students, show a smaller improvement in probability of enrolling in Utah higher education than do ECHS students – the differences may be attributed to these students' investment in Utah higher education.

Perhaps the most enduring benefit of participation in dual-credit enrollment programs involves the household endowment effect with respect to education. We sometimes forget that gains from education policy often occur over decades and while they may also be reflected in the productivity of any given student, their most meaningful impact may be experienced generations in the future. Our society's current focus on postsecondary or higher education completion is made possible by the high school movement of the early 20th century, prior to which only higher performing or economically advantaged students participated in secondary education. Similarly, it wasn't until the latter part of the same century that higher education began to become accessible to the masses. The public policy resulting in these advancements in human capital investment not only set the stage for the golden age of capitalism, but also led to household level endowments that would motivate yet higher levels of investment for future generations. In similar fashion, as dual-credit enrollment programs, the roots of which may be found in the early 1970s, result in higher rates of educational participation and attainment, they set the stage for future generations of households with higher incomes, parents whose college degrees form expectations for their children, and young people with the preparation and perspective to reach for greater levels of innovation and productivity.

## Future Research

The popularity of dual-credit programs motivates additional research beyond that which is examined and presented in this study. Among these are issues with respect to the effects of accumulated levels of higher education course credits rather than binary program participation, the effects of higher education course availability and requirements based on academic major on time-to-completion and cost-to-completion, the average treatment effect on the control (untreated) as an externality of dual-credit program fulfillment, and numerous other interesting and policy impacting issues.

Utah's Education Longitudinal Data are rich and offer a compelling resource for future data examinations. Motivated by increasing interest in dual-credit enrollment programs as reforms in secondary education, these data hold important information regarding the relationship between these programs and labor market outcomes, how the intensity of program participation - as measured by accumulated higher education credit hours – relates to higher education and labor market outcomes, and how today's education policy affects tomorrows household endowment effect with respect to education. Each of these issues may be researched in time of course, and each potentially yields information critical to making future education policy decisions.

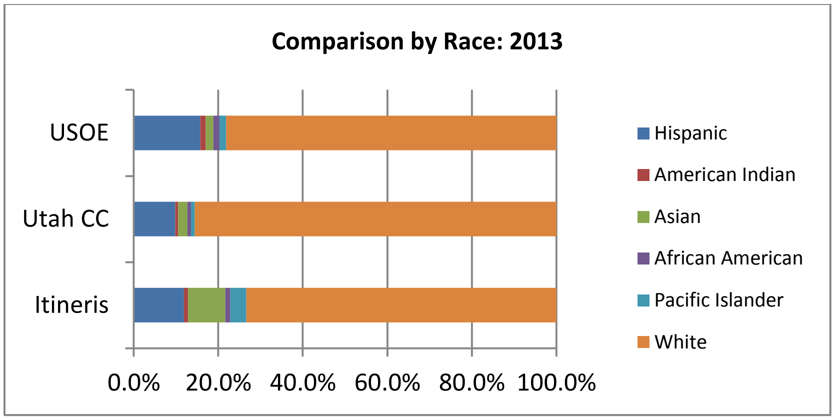


**Figure 7.1 Comparison by Race: 2013**

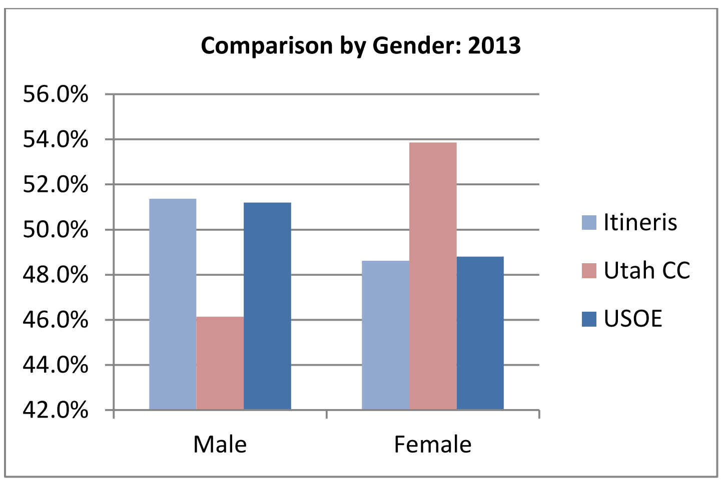


**Figure 7.2 Comparison by Gender**

# APPENDIX A

# MIDDLE COLLEGE AND EARLY COLLEGE HIGH SCHOOL

# PARAMETERS

**Middle College Model (Lieberman 2004)**

1. Total enrollment of no more than 450 students
2. Location on a college campus provides motivation and mitigates usual teenage behavior. As such high school students develop a "future orientation." Sharing the college facilities—gym, library, cafeteria—enhances the resources of the high school, provides better institutional utilization, and shares costs.
3. Shared space, including teenagers on the college campus, reduces the traditional fears of college faculty toward teaching younger students and helps encourage collaboration between high school and college faculty.
4. Operating a high school function on a college schedule requires changes in traditional high school structures, requires longer classes, enables project learning and portfolio assessment, and encourages personal freedom. High school students are treated as adults: There are no bells, no hall monitors, and no metal detectors. There are personal responsibility, trust, and encouragement.
5. High school faculty have an enhanced role. They gain privileges of college faculty, better facilities, private offices, personal telephones, professional respect, and the opportunity to teach at the college level.
6. Middle College enables and encourages more intensive guidance, with a ratio of 3 counselors to 450 students.
7. Students receive daily peer and group counseling, with a high ratio of paraprofessionals to students.

8. A program of internship is encouraged: Work in the community for students offers 25%-33% of the school population a program of learning off campus; reducing the in-school population on specific days.
9. The calendar is based on the college schedule.

**Early College High School Model (Lieberman 2004)**

1. Reaches out for students who are undeserved by the regular schools;
2. Demands a cooperative relationship between the district high school administration and the college president;
3. Offers a different sequence of courses from the $10^{th}$ grade and an accelerated program from the $9^{th}$ grade to the Associate's Degree, which can be achieved in 5 years or less, instead of 6;
4. Combines the resources of a high school on the college campus with the college facilities (gym, library, cafeteria), making them all available to the Early College High School student;
5. Requires active college campus collaboration from the college administrative structure: faculty interchange, support from the college divisions of finance, admissions, scheduling, and counseling under a college-appointed administrator;
6. Enhances the role of high school faculty;
7. Integrates high school and college study in an articulated program.

# APPENDIX B

# VARIABLE TABLES AND SOURCES

| **Data table name: k12 assessment2008 k12assessment2009** | | **Data source: USOE** | |
|---|---|---|---|
| **Variable name (UDA assigned)** | **Variable name (given)** | **Variable description (short)** | **Variable type** |
| personid | personid | unique individual identification number | discrete |
| k12_id | k12_id | Enrolled in Utah Public K12 | binary |
| k12_graduated_ind | k12_graduated_ind | Graduated from Utah K12 | binary |
| ushe_ind | ushe_ind | Enrolled in Utah Higher Education | binary |
| ushe_graduated_ind | ushe_grad | Graduated from Utah Higher Education | binary |
| dws_ever_ui | dws_ui | Student household qualified for Utah unemployment benefits while student enrolled in Utah public primary or secondary education | binary |
| birth_date | b_date | Student date of birth | Date |
| all_race | race | Self-reported student race by category | discrete |
| all_gender | gender | Student gender | binary |
| k12_ever_low_income | k12_ever_low_income | Student qualified for Utah free lunch (meals) program while student enrolled in Utah public education | binary |
| k12_ever_ell | k12_ever_ell | Student enrolled in English Language Learner program while enrolled in Utah public education | binary |
| k12_ever_special_ed | k12_ever_special_ed | Student enrolled in Special Education program while enrolled in Utah public education | binary |
| k12_ever_mobile | k12_ever_mobile | Student changed schools mid program while enrolled in Utah public education | binary |
| assessment_min_score | assess_min | Minimum score for target assessment tests | continuous |
| assessment_max_score | assess_max | Maximum score for target assessment tests | continuous |
| assessment_pass_ind | assess_pass | Assessment test pass/fail indicator | binary |
| assessment_score | assessment_score | Student standardized test score based on test type | continuous |
| assessment_score_type | assess_score | Student standardized test score type | label |
| assessment_sub_test | assess_test | Standardized test subtype | label |
| assessment_subject_area | assess_subject | Standardized test subject area | label |
| assessment_type | assess_type | Student standardized test type | label |
| attempt | attempt | Numbered attempt at standardized test (1,2,3…) | discrete |

| Variable name (UDA assigned) | Variable name (given) | Variable description (short) | Variable type |
|---|---|---|---|
| firstattemptind | first_attempt | Date of first standardized test attempt | Date |
| test_taken_timeperiod | test_taken_timeperiod | Time period in which standardized test taken | discrete |
| timeperiod_id | timeperiod_id | ID number for time period in which standardized test taken | discrete |
| unified_year | year | Year standardized test taken | discrete |

**Data table name: k12dws2008**
**k12dws2009**

**Data source: UT DWFS**

| Variable name (UDA assigned) | Variable name (given) | Variable description (short) | Variable type |
|---|---|---|---|
| personid | personid | Statewide Student Identified | discrete |
| k12_id | k12_id | Enrolled in Utah Public K12 | binary |
| k12_graduated_ind | k12_graduated_ind | Graduated from Utah K12 | binary |
| ushe_ind | ushe_ind | Enrolled in Utah Higher Education | binary |
| ushe_graduated_ind | ushe_grad | Graduated from Utah Higher Education | binary |
| dws_ever_ui | dws_ui | Student household qualified for Utah unemployment benefits while student enrolled in Utah public primary or secondary education | binary |
| birth_date | b_date | Student date of birth | Date |
| all_race | race | Self-reported student race by category | discrete |
| all_gender | gender | Student gender | binary |
| k12_ever_low_income | k12_ever_low_income | Student qualified for Utah free lunch (meals) program while student enrolled in Utah public education | binary |
| k12_ever_ell | k12_ever_ell | Student enrolled in English Language Learner program while enrolled in Utah public education | binary |
| k12_ever_special_ed | k12_ever_special_ed | Student enrolled in Special Education program while enrolled in Utah public education | binary |
| k12_ever_mobile | k12_ever_mobile | Student changed schools mid program while enrolled in Utah public education | binary |
| calendar_quarter_code | calendar_quarter_code | Calendar quarter of wage report | discrete |

| Variable name (UDA assigned) | Variable name (given) | Variable description (short) | Variable type |
|---|---|---|---|
| calendar_quarter_code_description | calendar_quarter_code_description | Description of calendar quarter of wage report | label |
| calendar_year | calendar_year | Year of wage report | discrete |
| unified_year | unified_year | Year of wage report | discrete |
| wages | wages | Dollar amount of reported wages | continuous |
| industry_2_digit_code | industry_code_2 | 2 digit industry classification code | discrete |
| industry_2_digit_desc | industry_2_digit_desc | Description of 2 digit industry classification code | label |
| industry_2_digit_id | industry_2_digit_id | ID # of 2 digit industry classification code | discrete |
| industry_3_digit_code | industry_code_3 | 3 digit industry classification code | discrete |
| industry_3_digit_desc | industry_3_digit_desc | Description of 3 digit industry classification code | label |
| industry_3_digit_id | industry_3_digit_id | ID # of 3 digit industry classification code | discrete |

**Data table: k12graduation2008**
**k12graduation2009**

**Data source: USOE**

| Variable name (UDA assigned) | Variable name (given) | Variable description (short) | Variable type |
|---|---|---|---|
| personid | personid | Statewide Student Identified | discrete |
| k12_id | k12_id | Enrolled in Utah Public K12 | binary |
| k12_graduated_ind | k12_graduated_ind | Graduated from Utah K12 | binary |
| ushe_ind | ushe_ind | Enrolled in Utah Higher Education | binary |
| ushe_graduated_ind | ushe_grad | Graduated from Utah Higher Education | binary |
| dws_ever_ui | dws_ui | Student household qualified for Utah unemployment benefits while student enrolled in Utah public primary or secondary education | binary |
| birth_date | b_date | Student date of birth | Date |
| all_race | race | Self-reported student race by category | discrete |
| all_gender | gender | Student gender | binary |
| k12_ever_low_income | k12_ever_low_income | Student qualified for Utah free lunch (meals) program while student enrolled in Utah public education | binary |
| k12_ever_ell | k12_ever_ell | Student enrolled in English Language Learner program while enrolled in Utah public education | binary |

| Variable name (UDA assigned) | Variable name (given) | Variable description (short) | Variable type |
|---|---|---|---|
| k12_ever_special_ed | k12_ever_special_ed | Student enrolled in Special Education program while enrolled in Utah public education | binary |
| k12_ever_mobile | k12_ever_mobile | Student changed schools mid program while enrolled in Utah public education | binary |
| limited_english_ind | limited_english_ind | Student identified as limited English speaker | binary |
| low_income_ind | low_income_ind | Student household identified as low income | binary |
| migrant | migrant | Student identified as migrant | binary |
| mobile_ind | mobile_ind | Student identified as mobile | binary |
| sped_ind | sped_ind | Student identified as Special Education | binary |
| district_id | district_id | District ID # - UDA/UEN | discrete |
| district_name | district_name | District name | label |
| district_number | dist_number | District ID # - State | discrete |
| entry_date | entry | Date student enrolled in Utah public education | Date |
| exit_date | exit | Date student exited Utah public education | Date |
| high_school_completion_status_code | hs_complete_code | High school completion code | discrete |
| high_school_completion_status_description | high_school_completion_status_description | High school completion status | label |
| school_id | school_id | High school ID # - UDA/UEN | discrete |
| school_name | school_name | High school name | label |
| school_number | hs_number | High school ID # - State | discrete |

**Data table name: k12highered2008**
**k12highered2009**

**Data source: USHE**

| Variable name (UDA assigned) | Variable name (given) | Variable description (short) | Variable type |
|---|---|---|---|
| personid | personid | Statewide Student Identified | discrete |
| k12_id | k12_id | Enrolled in Utah Public K12 | binary |
| k12_graduated_ind | k12_graduated_ind | Graduated from Utah K12 | binary |
| ushe_ind | ushe_ind | Enrolled in Utah Higher Education | binary |
| ushe_graduated_ind | ushe_grad | Graduated from Utah Higher Education | binary |

| **Variable name (UDA assigned)** | **Variable name (given)** | **Variable description (short)** | **Variable type** |
|---|---|---|---|
| dws_ever_ui | dws_ui | Student household qualified for Utah unemployment benefits while student enrolled in Utah public primary or secondary education | binary |
| birth_date | b_date | Student date of birth | Date |
| all_race | race | Self-reported student race by category | discrete |
| all_gender | gender | Student gender | binary |
| k12_ever_low_income | k12_ever_low_incom e | Student qualified for Utah free lunch (meals) program while student enrolled in Utah public education | binary |
| k12_ever_ell | k12_ever_ell | Student enrolled in English Language Learner program while enrolled in Utah public education | binary |
| k12_ever_special_ed | k12_ever_special_ed | Student enrolled in Special Education program while enrolled in Utah public education | binary |
| k12_ever_mobile | k12_ever_mobile | Student changed schools mid program while enrolled in Utah public education | binary |
| k12_entry_date | entry | Higher education entry date | date |
| institution_code | institution_code | Higher education institution code | discrete |
| institution_name | institution_name | Higher education institution name | label |
| enrollment_type_code | enroll_type | Higher education enrollment type | discrete |
| enrollment_type_description | enrollment_type_des cription | Higher education enrollment description | label |
| enrollment_status_code | enroll_status | Higher educating enrollment status code | discrete |
| enrollment_status_description | enrollment_status_de scription | Higher educating enrollment status description | label |
| credits_ap_total | credit_ap | AP Credits | continues |
| credits_clep_total | credit_clep | CLEP credits | continues |
| credits_transferred_total | credit_trans | Transferred higher education credits | continues |
| cum_hrs_ugrad | cumm_hrs_ugrad | Cumulative higher education credit hours - undergraduate | continues |
| cum_gpa_ugrad | cumm_gpa_ugrad | Cumulative higher education GPA - undergraduate | continues |

| **Data table name: k12higheredgraduation2008 k12higheredgraduation2009** | | **Data source: USHE** | |
|---|---|---|---|
| **Variable name (UDA assigned)** | **Variable name (given)** | **Variable description (short)** | **Variable type** |
| personid | personid | Statewide Student Identified | discrete |
| k12_id | k12_id | Enrolled in Utah Public K12 | binary |
| k12_graduated_ind | k12_graduated_ind | Graduated from Utah K12 | binary |
| ushe_ind | ushe_ind | Enrolled in Utah Higher Education | binary |
| ushe_graduated_ind | ushe_grad | Graduated from Utah Higher Education | binary |
| dws_ever_ui | dws_ui | Student household qualified for Utah unemployment benefits while student enrolled in Utah public primary or secondary education | binary |
| birth_date | b_date | Student date of birth | Date |
| all_race | race | Self-reported student race by category | discrete |
| all_gender | gender | Student gender | binary |
| k12_ever_low_income | k12_ever_low_income | Student qualified for Utah free lunch (meals) program while student enrolled in Utah public education | binary |
| k12_ever_ell | k12_ever_ell | Student enrolled in English Language Learner program while enrolled in Utah public education | binary |
| k12_ever_special_ed | k12_ever_special_ed | Student enrolled in Special Education program while enrolled in Utah public education | binary |
| k12_ever_mobile | k12_ever_mobile | Student changed schools mid program while enrolled in Utah public education | binary |
| institution_code | institution_code | Higher education institution code | discrete |
| institution_name | institution_name | Higher education institution name | label |
| graduation_date | grad_date | Higher education graduation date | date |
| degree_code | he_degree | Higher education degree code | discrete |
| cip_code | cip_code | CIP code | discrete |
| cip_code_description | cip_code_description | CIP description | label |

# APPENDIX C

# RECEIVER OPERATING CHARACTERISTIC ANALYSIS

## Underrepresented Student Population ROC Analysis

| Model | Subgroup | AUC |
|---|---|---|
| K12 GRAD | ELL | 0.752 |
| DCE | FEMALE | 0.775 |
| Probit | LOW INCOME | 0.749 |
| NN = 1 | LOW INCOME FEMALE | 0.686 |
| | LOW INCOME MALE | 0.754 |
| | MALE | 0.779 |
| | MINORITY | 0.690 |
| | MINORITY FEMALE | 0.691 |
| | MINORITY MALE | 0.697 |
| K12 GRAD | ELL | NSO |
| ECHS | FEMALE | 0.709 |
| Probit | LOW INCOME | 0.686 |
| NN = 1 | LOW INCOME FEMALE | 0.664 |
| | LOW INCOME MALE | 0.763 |
| | MALE | 0.711 |
| | MINORITY | 0.789 |
| | MINORITY FEMALE | 0.762 |
| | MINORITY MALE | 0.712 |
| POST ENROLL | ELL | 0.725 |
| DCE | FEMALE | 0.774 |
| Probit | LOW INCOME | 0.766 |
| NN = 1 | LOW INCOME FEMALE | 0.772 |
| | LOW INCOME MALE | 0.741 |
| | MALE | 0.765 |
| | MINORITY | 0.734 |
| | MINORITY FEMALE | 0.755 |
| | MINORITY MALE | 0.748 |
| POST ENROLL | ELL | 0.727 |
| ECHS | FEMALE | 0.760 |
| Probit | LOW INCOME | 0.731 |
| NN = 1 | LOW INCOME FEMALE | 0.782 |
| | LOW INCOME MALE | 0.847 |
| | MALE | 0.744 |
| | MINORITY | 0.798 |
| | MINORITY FEMALE | 0.705 |
| | MINORITY MALE | 0.806 |
| USHE GRAD | ELL | 0.923 |
| DCE | FEMALE | 0.842 |
| Probit | LOW INCOME | 0.905 |
| NN = 1 | LOW INCOME FEMALE | 0.849 |
| | LOW INCOME MALE | 0.948 |
| | MALE | 0.938 |
| | MINORITY | 0.895 |
| | MINORITY FEMALE | 0.909 |
| | MINORITY MALE | NSO |
| USHE GRAD | ELL | 0.774 |
| ECHS | FEMALE | 0.805 |
| Probit | LOW INCOME | 0.891 |
| NN = 1 | LOW INCOME FEMALE | 0.878 |
| | LOW INCOME MALE | 0.957 |
| | MALE | 0.965 |
| | MINORITY | 0.844 |
| | MINORITY FEMALE | 0.908 |
| | MINORITY MALE | 0.909 |

| Model | Subgroup | AUC |
|---|---|---|
| USHE_ASSOC | ELL | 0.715 |
| DCE | FEMALE | 0.754 |
| Probit | LOW INCOME | 0.782 |
| NN = 1 | LOW INCOME FEMALE | 0.731 |
| | LOW INCOME MALE | 0.818 |
| | MALE | 0.757 |
| | MINORITY | 0.693 |
| | MINORITY FEMALE | 0.786 |
| | MINORITY MALE | 0.646 |
| USHE_ASSOC | ELL | 0.470 |
| ECHS | FEMALE | 0.757 |
| Probit | LOW INCOME | 0.709 |
| NN = 1 | LOW INCOME FEMALE | 0.739 |
| | LOW INCOME MALE | 0.729 |
| | MALE | 0.717 |
| | MINORITY | 0.720 |
| | MINORITY FEMALE | 0.749 |
| | MINORITY MALE | NSO |
| USHE_BACH | ELL | 0.765 |
| DCE | FEMALE | 0.728 |
| Probit | LOW INCOME | 0.792 |
| NN = 1 | LOW INCOME FEMALE | 0.763 |
| | LOW INCOME MALE | 0.831 |
| | MALE | 0.796 |
| | MINORITY | 0.649 |
| | MINORITY FEMALE | 0.747 |
| | MINORITY MALE | 0.666 |
| USHE_BACH | ELL | 0.819 |
| ECHS | FEMALE | 0.693 |
| Probit | LOW INCOME | 0.685 |
| NN = 1 | LOW INCOME FEMALE | 0.654 |
| | LOW INCOME MALE | NSO |
| | MALE | 0.830 |
| | MINORITY | 0.718 |
| | MINORITY FEMALE | 0.692 |
| | MINORITY MALE | 0.581 |
| T2C_ASSOC | FEMALE | 0.813 |
| DCE | MINORITY | 0.891 |
| Logit | MALE | 0.938 |
| NN = 1 | INCOME | 0.901 |
| | ELL | 0.735 |
| | MINORITY MALE | 0.931 |
| | MINORITY FEMALE | 0.900 |
| | LOW INCOME MALE | 0.945 |
| | LOW INCOME FEMALE | 0.830 |
| T2C_ASSOC | FEMALE | 0.892 |
| ECHS | MINORITY | 0.600 |
| Logit | MALE | 0.813 |
| NN = 1 | INCOME | 0.917 |
| | ELL | 0.735 |
| | MINORITY MALE | NSO |
| | MINORITY FEMALE | 0.871 |
| | LOW INCOME MALE | 0.774 |
| | LOW INCOME FEMALE | 0.815 |

| Model | Subgroup | AUC |
|---|---|---|
| T2C_BACH | FEMALE | 0.852 |
| DCE | MINORITY | 0.854 |
| Logit | MALE | 0.745 |
| NN = 1 | INCOME | 0.747 |
| | ELL | 0.846 |
| | MINORITY MALE | 0.976 |
| | MINORITY FEMALE | 0.912 |
| | LOW INCOME MALE | 0.845 |
| | LOW INCOME FEMALE | 0.810 |
| T2C_BACH | FEMALE | 0.809 |
| ECHS | MINORITY | NSO |
| Logit | MALE | 0.866 |
| NN = 1 | INCOME | 0.707 |
| | ELL | NSO |
| | MINORITY MALE | 0.871 |
| | MINORITY FEMALE | 0.537 |
| | LOW INCOME MALE | 0.816 |
| | LOW INCOME FEMALE | 0.898 |
| ACT_COMP | FEMALE | 0.685 |
| DCE | MINORITY | 0.722 |
| Logit | MALE | 0.685 |
| NN = 1 | INCOME | 0.705 |
| | ELL | 0.713 |
| | MINORITY MALE | 0.685 |
| | MINORITY FEMALE | 0.702 |
| | LOW INCOME MALE | 0.689 |
| | LOW INCOME FEMALE | 0.645 |
| ACT_COMP | FEMALE | 0.616 |
| ECHS | MINORITY | 0.742 |
| Logit | MALE | 0.827 |
| NN = 1 | INCOME | 0.682 |
| | ELL | 0.773 |
| | MINORITY MALE | 0.764 |
| | MINORITY FEMALE | 0.720 |
| | LOW INCOME MALE | 0.824 |
| | LOW INCOME FEMALE | 0.592 |

**Model includes: Outcome, Treatment, Form, Nearest Neighbor Match**

**NSO: Insufficient Observation for form AUC**

## General Student Population Analysis

| Model | | Model | | Pretreatment Exclusions | | | | | N N | Form | AUC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Outcome | Treatment | | | Mobile | Income | ELL | Gender | Race | | | |
| K12 GRAD | DCE | A | 1 | | | | | | 1 | Probit | 0.681 |
| | | A | 2 | | | | | | 2 | Probit | 0.630 |
| | | A | 3 | | | | | | 3 | Probit | NSO |
| | | A | 4 | X | | | | | 1 | Probit | 0.778 |
| | | A | 5 | X | | | | | 2 | Probit | 0.519 |
| | | A | 6 | X | | | | | 3 | Probit | 0.787 |
| | | A | 7 | X | X | | | | 1 | Probit | 0.787 |
| | | A | 8 | X | | X | | | 1 | Probit | 0.778 |
| | | A | 9 | X | | | X | | 1 | Probit | 0.785 |
| | | A | 10 | X | | | | X | 1 | Probit | 0.779 |
| | | | | | | | | | | | |
| K12 GRAD | ECHS | B | 1 | | | | | | 1 | Probit | 0.820 |
| | | B | 2 | | | | | | 2 | Probit | 0.400 |
| | | B | 3 | | | | | | 3 | Probit | NSO |
| | | B | 4 | X | | | | | 1 | Probit | 0.766 |
| | | B | 5 | X | | | | | 2 | Probit | 0.476 |
| | | B | 6 | X | | | | | 3 | Probit | 0.841 |
| | | B | 7 | X | X | | | | 1 | Probit | 0.358 |
| | | B | 8 | X | | X | | | 1 | Probit | 0.832 |
| | | B | 9 | X | | | X | | 1 | Probit | 0.791 |
| | | B | 10 | X | | | | X | 1 | Probit | 0.654 |
| | | | | | | | | | | | |
| POST_ENROLL | DCE | C | 1 | | | | | | 1 | Probit | 0.750 |
| | | C | 2 | | | | | | 2 | Probit | 0.903 |
| | | C | 3 | | | | | | 3 | Probit | 0.882 |
| | | C | 4 | X | | | | | 1 | Probit | 0.770 |
| | | C | 5 | X | | | | | 2 | Probit | 0.912 |
| | | C | 6 | X | | | | | 3 | Probit | 0.903 |
| | | C | 7 | X | X | | | | 1 | Probit | 0.785 |
| | | C | 8 | X | | X | | | 1 | Probit | 0.771 |
| | | C | 9 | X | | | X | | 1 | Probit | 0.788 |
| | | C | 10 | X | | | | X | 1 | Probit | 0.772 |
| | | | | | | | | | | | |
| POST_ENROLL | ECHS | D | 1 | | | | | | 1 | Probit | 0.748 |
| | | D | 2 | | | | | | 2 | Probit | 0.902 |
| | | D | 3 | | | | | | 3 | Probit | 0.856 |
| | | D | 4 | X | | | | | 1 | Probit | 0.780 |
| | | D | 5 | X | | | | | 2 | Probit | 0.920 |
| | | D | 6 | X | | | | | 3 | Probit | 0.910 |
| | | D | 7 | X | X | | | | 1 | Probit | 0.770 |
| | | D | 8 | X | | X | | | 1 | Probit | 0.722 |
| | | D | 9 | X | | | X | | 1 | Probit | 0.786 |
| | | D | 10 | X | | | | X | 1 | Probit | 0.770 |

| Model | | Model | | Pretreatment Exclusions | | | | | N N | Form | AUC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Outcome | Treatment | | | Mobile | Income | ELL | Gender | Race | | | |
| USHE_GRAD | DCE | E | 1 | | | | | | 1 | Probit | 0.886 |
| | | E | 2 | | | | | | 2 | Probit | 0.981 |
| | | E | 3 | | | | | | 3 | Probit | 0.994 |
| | | E | 4 | X | | | | | 1 | Probit | 0.889 |
| | | E | 5 | X | | | | | 2 | Probit | 0.989 |
| | | E | 6 | X | | | | | 3 | Probit | 0.997 |
| | | E | 7 | X | X | | | | 1 | Probit | 0.906 |
| | | E | 8 | X | | X | | | 1 | Probit | 0.884 |
| | | E | 9 | X | | | X | | 1 | Probit | 0.917 |
| | | E | 10 | X | | | | X | 1 | Probit | 0.896 |
| | | | | | | | | | | | |
| USHE_GRAD | ECHS | F | 1 | | | | | | 1 | Probit | 0.869 |
| | | F | 2 | | | | | | 2 | Probit | 0.979 |
| | | F | 3 | | | | | | 3 | Probit | 0.997 |
| | | F | 4 | X | | | | | 1 | Probit | 0.918 |
| | | F | 5 | X | | | | | 2 | Probit | 0.973 |
| | | F | 6 | X | | | | | 3 | Probit | NSO |
| | | F | 7 | X | X | | | | 1 | Probit | 0.878 |
| | | F | 8 | X | | X | | | 1 | Probit | 0.899 |
| | | F | 9 | X | | | X | | 1 | Probit | 0.888 |
| | | F | 10 | X | | | | X | 1 | Probit | 0.872 |
| | | | | | | | | | | | |
| USHE_ASSOC | DCE | G | 1 | | | | | | 1 | Probit | 0.785 |
| | | G | 2 | | | | | | 2 | Probit | 0.920 |
| | | G | 3 | | | | | | 3 | Probit | 0.966 |
| | | G | 4 | X | | | | | 1 | Probit | 0.743 |
| | | G | 5 | X | | | | | 2 | Probit | 0.926 |
| | | G | 6 | X | | | | | 3 | Probit | 0.976 |
| | | G | 7 | X | X | | | | 1 | Probit | 0.741 |
| | | G | 8 | X | | X | | | 1 | Probit | 0.717 |
| | | G | 9 | X | | | X | | 1 | Probit | 0.731 |
| | | G | 10 | X | | | | X | 1 | Probit | 0.735 |
| | | | | | | | | | | | |
| USHE_ASSOC | ECHS | H | 1 | | | | | | 1 | Probit | 0.745 |
| | | H | 2 | | | | | | 2 | Probit | 0.945 |
| | | H | 3 | | | | | | 3 | Probit | 0.985 |
| | | H | 4 | X | | | | | 1 | Probit | 0.747 |
| | | H | 5 | X | | | | | 2 | Probit | 0.890 |
| | | H | 6 | X | | | | | 3 | Probit | 0.966 |
| | | H | 7 | X | X | | | | 1 | Probit | 0.712 |
| | | H | 8 | X | | X | | | 1 | Probit | 0.684 |
| | | H | 9 | X | | | X | | 1 | Probit | 0.717 |
| | | H | 10 | X | | | | X | 1 | Probit | 0.736 |
| | | | | | | | | | | | |
| USHE_BACH | DCE | I | 1 | | | | | | 1 | Probit | 0.736 |
| | | I | 2 | | | | | | 2 | Probit | 0.932 |

| Model | | Model | | Pretreatment Exclusions | | | | | N<br>N | Form | AUC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Outcome | Treatment | | | Mobile | Income | ELL | Gender | Race | | | |
| | | I | 3 | | | | | | 3 | Probit | 0.980 |
| | | I | 4 | X | | | | | 1 | Probit | 0.760 |
| | | I | 5 | X | | | | | 2 | Probit | 0.934 |
| | | I | 6 | X | | | | | 3 | Probit | 0.978 |
| | | I | 7 | X | X | | | | 1 | Probit | 0.738 |
| | | I | 8 | X | | X | | | 1 | Probit | 0.741 |
| | | I | 9 | X | | | X | | 1 | Probit | 0.753 |
| | | I | 10 | X | | | | X | 1 | Probit | 0.737 |
| | | | | | | | | | | | |
| USHE_BACH | ECHS | J | 1 | | | | | | 1 | Probit | 0.657 |
| | | J | 2 | | | | | | 2 | Probit | 0.860 |
| | | J | 3 | | | | | | 3 | Probit | 0.968 |
| | | J | 4 | X | | | | | 1 | Probit | 0.691 |
| | | J | 5 | X | | | | | 2 | Probit | 0.895 |
| | | J | 6 | X | | | | | 3 | Probit | 0.965 |
| | | J | 7 | X | X | | | | 1 | Probit | 0.705 |
| | | J | 8 | X | | X | | | 1 | Probit | 0.691 |
| | | J | 9 | X | | | X | | 1 | Probit | 0.785 |
| | | J | 10 | X | | | | X | 1 | Probit | 0.710 |
| | | | | | | | | | | | |
| T2C_ASSOC | DCE | A | 1 | | | | | | 1 | Logit | 0.852 |
| | | A | 2 | | | | | | 2 | Logit | 0.911 |
| | | A | 3 | | | | | | 3 | Logit | 0.932 |
| | | A | 4 | X | | | | | 1 | Logit | 0.832 |
| | | A | 5 | X | | | | | 2 | Logit | 0.905 |
| | | A | 6 | X | | | | | 3 | Logit | 0.929 |
| | | A | 7 | X | X | | | | 1 | Logit | 0.835 |
| | | A | 8 | X | | X | | | 1 | Logit | 0.846 |
| | | A | 9 | X | | | X | | 1 | Logit | 0.852 |
| | | A | 10 | X | | | | X | 1 | Logit | 0.838 |
| | | | | | | | | | | | |
| T2C_ASSOC | ECHS | B | 1 | | | | | | 1 | Logit | 0.906 |
| | | B | 2 | | | | | | 2 | Logit | 0.843 |
| | | B | 3 | | | | | | 3 | Logit | 0.961 |
| | | B | 4 | X | | | | | 1 | Logit | 0.910 |
| | | B | 5 | X | | | | | 2 | Logit | 0.957 |
| | | B | 6 | X | | | | | 3 | Logit | 0.984 |
| | | B | 7 | X | X | | | | 1 | Logit | 0.896 |
| | | B | 8 | X | | X | | | 1 | Logit | 0.885 |
| | | B | 9 | X | | | X | | 1 | Logit | 0.907 |
| | | B | 10 | X | | | | X | 1 | Logit | 0.916 |
| | | | | | | | | | | | |
| T2C_BACH | DCE | C | 1 | | | | | | 1 | Logit | 0.813 |
| | | C | 2 | | | | | | 2 | Logit | 0.848 |
| | | C | 3 | | | | | | 3 | Logit | 0.875 |

| **Mobile** | | **Mobile** | | **Pretreatment Variables** | | | | | **N N** | **Form** | **AUC** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Outcome** | **Treatment** | | | **Mobile** | **Income** | **ELL** | **Gender** | **Race** | | | |
| | | C | 4 | X | | | | | 1 | Logit | 0.805 |
| | | C | 5 | X | | | | | 2 | Logit | 0.822 |
| | | C | 6 | X | | | | | 3 | Logit | 0.845 |
| | | C | 7 | X | X | | | | 1 | Logit | 0.815 |
| | | C | 8 | X | | X | | | 1 | Logit | 0.808 |
| | | C | 9 | X | | | X | | 1 | Logit | 0.819 |
| | | C | 10 | X | | | | X | 1 | Logit | 0.794 |
| | | | | | | | | | | | |
| T2C_BACH | ECHS | D | 1 | | | | | | 1 | Logit | 0.870 |
| | | D | 2 | | | | | | 2 | Logit | 0.876 |
| | | D | 3 | | | | | | 3 | Logit | 0.922 |
| | | D | 4 | X | | | | | 1 | Logit | 0.829 |
| | | D | 5 | X | | | | | 2 | Logit | 0.898 |
| | | D | 6 | X | | | | | 3 | Logit | 0.951 |
| | | D | 7 | X | X | | | | 1 | Logit | 0.910 |
| | | D | 8 | X | | X | | | 1 | Logit | 0.832 |
| | | D | 9 | X | | | X | | 1 | Logit | 0.845 |
| | | D | 10 | X | | | | X | 1 | Logit | 0.867 |
| | | | | | | | | | | | |
| ACT_COMP | DCE | E | 1 | | | | | | 1 | Logit | 0.710 |
| | | E | 2 | | | | | | 2 | Logit | 0.743 |
| | | E | 3 | | | | | | 3 | Logit | 0.768 |
| | | E | 4 | X | | | | | 1 | Logit | 0.677 |
| | | E | 5 | X | | | | | 2 | Logit | 0.733 |
| | | E | 6 | X | | | | | 3 | Logit | 0.760 |
| | | E | 7 | X | X | | | | 1 | Logit | 0.680 |
| | | E | 8 | X | | X | | | 1 | Logit | 0.680 |
| | | E | 9 | X | | | X | | 1 | Logit | 0.661 |
| | | E | 10 | X | | | | X | 1 | Logit | 0.688 |
| | | | | | | | | | | | |
| ACT_COMP | ECHS | F | 1 | | | | | | 1 | Logit | 0.695 |
| | | F | 2 | | | | | | 2 | Logit | 0.761 |
| | | F | 3 | | | | | | 3 | Logit | 0.786 |
| | | F | 4 | X | | | | | 1 | Logit | 0.699 |
| | | F | 5 | X | | | | | 2 | Logit | 0.776 |
| | | F | 6 | X | | | | | 3 | Logit | 0.802 |
| | | F | 7 | X | X | | | | 1 | Logit | 0.761 |
| | | F | 8 | X | | X | | | 1 | Logit | 0.702 |
| | | F | 9 | X | | | X | | 1 | Logit | 0.694 |
| | | F | 10 | X | | | | X | 1 | Logit | 0.714 |

# APPENDIX D

# GENERAL STUDENT POPULATION TABLES (1-14.2)

**Outcome Table 1 - K12 Graduated (k12_graduated)**
**General Student Population**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.247 | 0.007 | 33.180 | 0.000 | 0.232 | 0.262 |
| 2009 | DCE | 0.201 | 0.006 | 31.610 | 0.000 | 0.189 | 0.214 |
| 2008 | ECHS | 0.198 | 0.021 | 9.530 | 0.000 | 0.157 | 0.239 |
| 2009 | ECHS | 0.220 | 0.017 | 13.170 | 0.000 | 0.188 | 0.253 |

**Outcome Table 2 - ACT Composite (act_composite)**
**General Student Population**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.319 | 0.072 | 4.460 | 0.000 | 0.179 | 0.460 |
| 2009 | DCE | 0.179 | 0.068 | 2.640 | 0.008 | 0.046 | 0.312 |
| 2008 | ECHS | 0.211 | 0.235 | 0.900 | 0.368 | -0.249 | 0.672 |
| 2009 | ECHS | 0.488 | 0.172 | 2.840 | 0.005 | 0.151 | 0.825 |

**Outcome Table 3 - ACT Math (act_math)**
**General Student Population**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | P>\|z\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.763 | 0.083 | 9.230 | 0.000 | 0.601 | 0.926 |
| 2009 | DCE | 0.508 | 0.079 | 6.430 | 0.000 | 0.353 | 0.662 |
| 2008 | ECHS | 0.664 | 0.276 | 2.400 | 0.016 | 0.123 | 1.205 |
| 2009 | ECHS | 0.632 | 0.204 | 3.100 | 0.002 | 0.232 | 1.031 |

**Outcome Table 4 - ACT English (act_english)**
**General Student Population**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.327 | 0.095 | 3.440 | 0.001 | 0.141 | 0.513 |
| 2009 | DCE | 0.047 | 0.091 | 0.520 | 0.605 | -0.131 | 0.225 |
| 2008 | ECHS | 0.384 | 0.300 | 1.280 | 0.201 | -0.205 | 0.973 |
| 2009 | ECHS | 0.517 | 0.231 | 2.240 | 0.025 | 0.065 | 0.969 |

**Outcome Table 5 - ACT Reading (act_reading)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.114 | 0.109 | -1.040 | 0.298 | -0.328 | 0.101 |
| 2009 | DCE | -0.123 | 0.098 | -1.260 | 0.207 | -0.315 | 0.068 |
| 2008 | ECHS | -0.539 | 0.337 | -1.600 | 0.109 | -1.199 | 0.120 |
| 2009 | ECHS | 0.172 | 0.230 | 0.750 | 0.456 | -0.280 | 0.623 |

**Outcome Table 6 - ACT Science (act_science)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.371 | 0.088 | 4.220 | 0.000 | 0.199 | 0.544 |
| 2009 | DCE | 0.274 | 0.079 | 3.470 | 0.001 | 0.119 | 0.429 |
| 2008 | ECHS | 0.426 | 0.244 | 1.740 | 0.081 | -0.053 | 0.905 |
| 2009 | ECHS | 0.642 | 0.198 | 3.240 | 0.001 | 0.254 | 1.029 |

**Outcome Table 7 - Post Secondary Higher Education Enrollment (post_enroll)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.288 | 0.009 | 31.92 | 0.000 | 0.270 | 0.306 |
| 2009 | DCE | 0.268 | 0.008 | 32.16 | 0.000 | 0.252 | 0.285 |
| 2008 | ECHS | 0.392 | 0.027 | 14.53 | 0.000 | 0.339 | 0.445 |
| 2009 | ECHS | 0.327 | 0.022 | 14.75 | 0.000 | 0.283 | 0.370 |

**Outcome Table 8 - Post Secondary Higher Education Enrollment (post_enroll_all)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.253 | 0.008 | 30.86 | 0.000 | 0.237 | 0.269 |
| 2009 | DCE | 0.223 | 0.008 | 29.42 | 0.000 | 0.208 | 0.238 |
| 2008 | ECHS | 0.310 | 0.023 | 13.22 | 0.000 | 0.264 | 0.357 |
| 2009 | ECHS | 0.268 | 0.018 | 15.07 | 0.000 | 0.233 | 0.303 |

**Outcome Table 9 - Higher Education Graduate (he_grad)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.147 | 0.010 | 14.600 | 0.000 | 0.127 | 0.166 |
| 2009 | DCE | 0.223 | 0.008 | 29.420 | 0.000 | 0.208 | 0.238 |
| 2008 | ECHS | 0.360 | 0.030 | 11.930 | 0.000 | 0.301 | 0.420 |
| 2009 | ECHS | 0.441 | 0.023 | 19.390 | 0.000 | 0.397 | 0.486 |

**Outcome Table 10 - Utah Higher Education Graduate (ushe_grad)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.084 | 0.008 | 10.910 | 0.000 | 0.069 | 0.099 |
| 2009 | DCE | 0.050 | 0.006 | 8.160 | 0.000 | 0.038 | 0.062 |
| 2008 | ECHS | 0.402 | 0.026 | 15.440 | 0.000 | 0.351 | 0.453 |
| 2009 | ECHS | 0.429 | 0.020 | 21.020 | 0.000 | 0.389 | 0.469 |

**Outcome Table 11 - Time-to-Completion: Associate's (t2c_assoc)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -262.30 | 29.415 | -8.920 | 0.000 | -319.95 | -204.65 |
| 2009 | DCE | -266.12 | 22.156 | -12.010 | 0.000 | -309.54 | -222.70 |
| 2008 | ECHS | -851.66 | 62.620 | -13.600 | 0.000 | -974.39 | -728.93 |
| 2009 | ECHS | -837.79 | 38.332 | -21.860 | 0.000 | -912.92 | -762.66 |

**Outcome Table 12 - Time-to-Completion: Bachelor's (t2c_bach)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -167.04 | 23.610 | -7.070 | 0.000 | -213.31 | -120.76 |
| 2009 | DCE | -188.94 | 30.663 | -6.160 | 0.000 | -249.04 | -128.84 |
| 2008 | ECHS | -249.17 | 48.169 | -5.170 | 0.000 | -343.58 | -154.76 |
| 2009 | ECHS | -316.94 | 56.075 | -5.650 | 0.00 | -426.84 | -207.03 |

**Outcome Table 13 - Highest HE Degree Attained: Associate's (high_degree_assoc)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: hgh_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.082 | 0.022 | 3.700 | 0.000 | 0.038 | 0.125 |
| 2009 | DCE | 0.127 | 0.024 | 5.210 | 0.000 | 0.079 | 0.174 |
| 2008 | ECHS | 0.131 | 0.043 | 3.050 | 0.002 | 0.047 | 0.215 |
| 2009 | ECHS | 0.137 | 0.038 | 3.610 | 0.00 | 0.063 | 0.212 |

**Outcome Table 13.2 - Highest USHE Degree Attained: Associate's (high_ushe_degree_assoc)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: high_ushe_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.105 | 0.020 | 5.130 | 0.000 | 0.065 | 0.145 |
| 2009 | DCE | 0.150 | 0.024 | 6.150 | 0.000 | 0.102 | 0.198 |
| 2008 | ECHS | 0.173 | 0.040 | 4.370 | 0.000 | 0.095 | 0.250 |
| 2009 | ECHS | 0.138 | 0.037 | 3.720 | 0.00 | 0.065 | 0.211 |

**Outcome Table 14 - Highest HE Degree Attained: Bachelor's (high_degree_bach)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: hgh_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.010 | 0.023 | 0.470 | 0.641 | -0.034 | 0.055 |
| 2009 | DCE | -0.001 | 0.023 | -0.060 | 0.952 | -0.047 | 0.044 |
| 2008 | ECHS | 0.011 | 0.043 | 0.260 | 0.798 | -0.073 | 0.094 |
| 2009 | ECHS | 0.010 | 0.036 | 0.290 | 0.77 | -0.060 | 0.081 |

**Outcome Table 14.2 - Highest HE Degree Attained: Bachelor's (high_ushe_degree_bach)**
**General Student Population**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: high_ushe_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.026 | 0.023 | 1.140 | 0.253 | -0.019 | 0.071 |
| 2009 | DCE | 0.020 | 0.022 | 0.920 | 0.356 | -0.023 | 0.064 |
| 2008 | ECHS | 0.048 | 0.039 | 1.220 | 0.221 | -0.029 | 0.126 |
| 2009 | ECHS | 0.027 | 0.035 | 0.780 | 0.44 | -0.042 | 0.097 |

# APPENDIX E

# UNDERREPRESENTED STUDENT TABLES: FEMALE (15 - 28)

**Outcome Table 15 - K12 Graduated (k12_graduated)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.241 | 0.010 | 23.520 | 0.000 | 0.221 | 0.261 |
| 2009 | DCE | 0.199 | 0.009 | 21.930 | 0.000 | 0.181 | 0.217 |
| | | | | | | | |
| 2008 | ECHS | 0.221 | 0.027 | 8.260 | 0.000 | 0.168 | 0.273 |
| 2009 | ECHS | 0.227 | 0.020 | 11.130 | 0.00 | 0.187 | 0.267 |

**Outcome Table 16 - ACT Composite (act_composite)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.207 | 0.090 | 2.300 | 0.022 | 0.030 | 0.384 |
| 2009 | DCE | 0.276 | 0.088 | 3.150 | 0.002 | 0.104 | 0.448 |
| 2008 | ECHS | 0.190 | 0.258 | 0.730 | 0.463 | -0.316 | 0.695 |
| 2009 | ECHS | 0.367 | 0.174 | 2.110 | 0.03 | 0.027 | 0.708 |

**Outcome Table 17 - ACT Math (act_math)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.500 | 0.102 | 4.910 | 0.000 | 0.301 | 0.700 |
| 2009 | DCE | 0.454 | 0.098 | 4.650 | 0.000 | 0.263 | 0.646 |
| 2008 | ECHS | 0.383 | 0.289 | 1.320 | 0.186 | -0.184 | 0.950 |
| 2009 | ECHS | 0.548 | 0.212 | 2.590 | 0.01 | 0.133 | 0.962 |

**Outcome Table 18 - ACT English (act_english)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.201 | 0.130 | 1.540 | 0.123 | -0.055 | 0.457 |
| 2009 | DCE | 0.300 | 0.119 | 2.510 | 0.012 | 0.066 | 0.534 |
| 2008 | ECHS | 0.642 | 0.349 | 1.840 | 0.066 | -0.041 | 1.326 |
| 2009 | ECHS | 0.476 | 0.246 | 1.930 | 0.05 | -0.006 | 0.958 |

**Outcome Table 19 - ACT Reading (act_reading)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.121 | 0.144 | -0.840 | 0.399 | -0.404 | 0.161 |
| 2009 | DCE | -0.036 | 0.130 | -0.270 | 0.783 | -0.291 | 0.220 |
| 2008 | ECHS | -0.237 | 0.406 | -0.580 | 0.560 | -1.032 | 0.559 |
| 2009 | ECHS | -0.041 | 0.263 | -0.160 | 0.88 | -0.556 | 0.473 |

**Outcome Table 20 - ACT Science (act_science)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.300 | 0.109 | 2.760 | 0.006 | 0.087 | 0.512 |
| 2009 | DCE | 0.348 | 0.098 | 3.540 | 0.000 | 0.155 | 0.540 |
| 2008 | ECHS | 0.013 | 0.306 | 0.040 | 0.966 | -0.586 | 0.612 |
| 2009 | ECHS | 0.478 | 0.220 | 2.170 | 0.03 | 0.046 | 0.909 |

**Outcome Table 21 - Post Secondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.300 | 0.109 | 2.760 | 0.006 | 0.087 | 0.512 |
| 2009 | DCE | 0.267 | 0.012 | 21.940 | 0.000 | 0.243 | 0.291 |
| 2008 | ECHS | 0.369 | 0.033 | 11.150 | 0.000 | 0.304 | 0.434 |
| 2009 | ECHS | 0.332 | 0.026 | 12.730 | 0.00 | 0.281 | 0.383 |

**Outcome Table 22 - Post Secondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.254 | 0.011 | 22.340 | 0.000 | 0.231 | 0.276 |
| 2009 | DCE | 0.220 | 0.011 | 20.280 | 0.000 | 0.198 | 0.241 |
| 2008 | ECHS | 0.290 | 0.028 | 10.190 | 0.000 | 0.234 | 0.346 |
| 2009 | ECHS | 0.273 | 0.021 | 12.740 | 0.00 | 0.231 | 0.314 |

| Outcome Table 23 - Utah Higher Education Graduate (he_grad) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Female | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: probit | | | |
| Outcome Model: matching | | | | Outcome Variable: he_grad | | | |
| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
| 2008 | DCE | 0.186 | 0.014 | 13.220 | 0.000 | 0.158 | 0.213 |
| 2009 | DCE | 0.137 | 0.013 | 10.640 | 0.000 | 0.111 | 0.162 |
| 2008 | ECHS | 0.317 | 0.038 | 8.420 | 0.000 | 0.244 | 0.391 |
| 2009 | ECHS | 0.427 | 0.028 | 15.190 | 0.00 | 0.372 | 0.483 |

| Outcome Table 24 - Utah Higher Education Graduate (ushe_grad) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Female | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: probit | | | |
| Outcome Model: matching | | | | Outcome Variable: ushe_grad | | | |
| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
| 2008 | DCE | 0.107 | 0.011 | 9.350 | 0.000 | 0.085 | 0.130 |
| 2009 | DCE | 0.043 | 0.011 | 3.880 | 0.000 | 0.021 | 0.064 |
| 2008 | ECHS | 0.337 | 0.032 | 10.370 | 0.000 | 0.273 | 0.400 |
| 2009 | ECHS | 0.417 | 0.026 | 16.300 | 0.00 | 0.367 | 0.467 |

| Outcome Table 25 - Time-to-Completion: Associate’s (t2c_assoc) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Female | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: logit | | | |
| Outcome Model: matching | | | | Outcome Variable: t2c_assoc | | | |
| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
| 2008 | DCE | -265.28 | 36.408 | -7.290 | 0.000 | -336.64 | -193.92 |
| 2009 | DCE | -210.88 | 26.727 | -7.890 | 0.000 | -263.27 | -158.50 |
| 2008 | ECHS | -647.11 | 60.961 | -10.620 | 0.000 | -766.59 | -527.63 |
| 2009 | ECHS | -776.18 | 42.581 | -18.23 | 0.000 | -859.64 | -692.72 |

| Outcome Table 26 - Time-to-Completion: Bachelor’s (t2c_bach) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Female | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: logit | | | |
| Outcome Model: matching | | | | Outcome Variable: t2c_bach | | | |
| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
| 2008 | DCE | -131.89 | 27.276 | -4.840 | 0.000 | -185.35 | -78.43 |
| 2009 | DCE | -235.91 | 32.058 | -7.360 | 0.000 | -298.74 | -173.08 |
| 2008 | ECHS | -278.79 | 58.435 | -4.770 | 0.000 | -393.31 | -164.26 |
| 2009 | ECHS | -325.77 | 45.252 | -7.200 | 0.000 | -414.46 | -237.07 |

**Outcome Table 27 - Highest HE Degree: Associate's (high_degree_assoc)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: high_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.052 | 0.028 | 1.890 | 0.059 | -0.002 | 0.106 |
| 2009 | DCE | 0.091 | 0.029 | 3.100 | 0.002 | 0.034 | 0.149 |
| 2008 | ECHS | 0.011 | 0.051 | 0.220 | 0.828 | -0.089 | 0.111 |
| 2009 | ECHS | 0.016 | 0.042 | 0.370 | 0.712 | -0.068 | 0.099 |

**Outcome Table 28 - Highest HE Degree: Bachelor's (high_degree_bach)**
**Underrepresented Student Population: Female**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: high_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.039 | 0.027 | 1.470 | 0.141 | -0.013 | 0.091 |
| 2009 | DCE | 0.020 | 0.025 | 0.780 | 0.435 | -0.030 | 0.070 |
| 2008 | ECHS | 0.051 | 0.049 | 1.040 | 0.299 | -0.045 | 0.147 |
| 2009 | ECHS | 0.124 | 0.039 | 3.230 | 0.001 | 0.049 | 0.200 |

**APPENDIX F**

**UNDERREPRESENTED STUDENT TABLES: MALE (29 - 42)**

**Outcome Table 29 - K12 Graduated (k12_graduated)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.248 | 0.010 | 24.040 | 0.000 | 0.228 | 0.268 |
| 2009 | DCE | 0.192 | 0.009 | 20.760 | 0.000 | 0.173 | 0.210 |
| 2008 | ECHS | 0.246 | 0.037 | 6.700 | 0.000 | 0.174 | 0.317 |
| 2009 | ECHS | 0.217 | 0.028 | 7.730 | 0.00 | 0.162 | 0.273 |

**Outcome Table 30 - ACT Composite (act_composite)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.261 | 0.109 | 2.410 | 0.016 | 0.048 | 0.474 |
| 2009 | DCE | 0.229 | 0.091 | 2.510 | 0.012 | 0.050 | 0.407 |
| 2008 | ECHS | 0.735 | 0.432 | 1.700 | 0.089 | -0.112 | 1.582 |
| 2009 | ECHS | 0.786 | 0.286 | 2.750 | 0.01 | 0.225 | 1.347 |

**Outcome Table 31 - ACT Math (act_math)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.539 | 0.137 | 3.940 | 0.000 | 0.271 | 0.807 |
| 2009 | DCE | 0.671 | 0.109 | 6.160 | 0.000 | 0.458 | 0.885 |
| 2008 | ECHS | 1.348 | 0.469 | 2.870 | 0.004 | 0.429 | 2.268 |
| 2009 | ECHS | 1.327 | 0.367 | 3.620 | 0.00 | 0.609 | 2.045 |

**Outcome Table 32 - ACT English (act_english)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.326 | 0.144 | 2.270 | 0.023 | 0.045 | 0.608 |
| 2009 | DCE | 0.054 | 0.129 | 0.420 | 0.676 | -0.200 | 0.308 |
| 2008 | ECHS | 0.288 | 0.529 | 0.540 | 0.586 | -0.749 | 1.325 |
| 2009 | ECHS | 0.618 | 0.401 | 1.540 | 0.12 | -0.169 | 1.404 |

**Outcome Table 33 - ACT Reading (act_reading)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.042 | 0.172 | 0.250 | 0.806 | -0.294 | 0.378 |
| 2009 | DCE | -0.019 | 0.132 | -0.140 | 0.888 | -0.278 | 0.241 |
| 2008 | ECHS | -0.015 | 0.598 | -0.030 | 0.980 | -1.187 | 1.157 |
| 2009 | ECHS | 0.455 | 0.382 | 1.190 | 0.234 | -0.295 | 1.205 |

**Outcome Table 34 - ACT Science (act_science)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.227 | 0.122 | 1.860 | 0.062 | -0.012 | 0.466 |
| 2009 | DCE | 0.238 | 0.110 | 2.170 | 0.030 | 0.023 | 0.453 |
| 2008 | ECHS | 1.386 | 0.475 | 2.920 | 0.004 | 0.456 | 2.317 |
| 2009 | ECHS | 0.763 | 0.319 | 2.390 | 0.017 | 0.138 | 1.389 |

**Outcome Table 35 - Postsecondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.280 | 0.013 | 22.260 | 0.000 | 0.255 | 0.305 |
| 2009 | DCE | 0.251 | 0.012 | 21.110 | 0.000 | 0.228 | 0.274 |
| 2008 | ECHS | 0.323 | 0.045 | 7.100 | 0.000 | 0.234 | 0.412 |
| 2009 | ECHS | 0.281 | 0.036 | 7.710 | 0.000 | 0.209 | 0.352 |

**Outcome Table 36 - Postsecondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.253 | 0.012 | 21.91 | 0.000 | 0.230 | 0.275 |
| 2009 | DCE | 0.209 | 0.011 | 18.99 | 0.000 | 0.188 | 0.231 |
| 2008 | ECHS | 0.309 | 0.041 | 7.530 | 0.000 | 0.229 | 0.390 |
| 2009 | ECHS | 0.218 | 0.031 | 7.050 | 0.000 | 0.158 | 0.279 |

**Outcome Table 37 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.100 | 0.011 | 9.140 | 0.000 | 0.079 | 0.122 |
| 2009 | DCE | 0.077 | 0.008 | 9.140 | 0.000 | 0.060 | 0.093 |
| 2008 | ECHS | 0.449 | 0.049 | 9.250 | 0.000 | 0.354 | 0.544 |
| 2009 | ECHS | 0.569 | 0.032 | 17.860 | 0.000 | 0.506 | 0.631 |

**Outcome Table 38 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.049 | 0.008 | 6.220 | 0.000 | 0.034 | 0.065 |
| 2009 | DCE | 0.035 | 0.006 | 5.640 | 0.000 | 0.023 | 0.047 |
| 2008 | ECHS | 0.427 | 0.038 | 11.210 | 0.000 | 0.353 | 0.502 |
| 2009 | ECHS | 0.466 | 0.030 | 15.560 | 0.000 | 0.407 | 0.524 |

**Outcome Table 39 - Time-to-Completion: Associate's (t2c_assoc)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -283.70 | 49.134 | -5.77 | 0.000 | -380.0 | -187.40 |
| 2009 | DCE | -372.56 | 37.924 | -9.82 | 0.000 | -446.8 | -298.23 |
| 2008 | ECHS | -1045.64 | 84.343 | -12.4 | 0.000 | -1210.9 | -880.33 |
| 2009 | ECHS | -940.96 | 53.661 | -17.5 | 0.000 | -1046.1 | -835.78 |

**Outcome Table 40 - Time-to-Completion: Bachelor's (t2c_bach)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -216.45 | 58.635 | -3.690 | 0.000 | -331.3 | -101.53 |
| 2009 | DCE | -189.63 | 82.078 | -2.310 | 0.021 | -350.5 | -28.76 |
| 2008 | ECHS | -44.50 | 74.527 | -0.600 | 0.550 | -190.5 | 101.57 |
| 2009 | ECHS | -383.71 | 137.477 | -2.790 | 0.005 | -653.1 | -114.26 |

**Outcome Table 41 - Highest HE Degree: Associate's (high_degree_assoc)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: high_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.137 | 0.040 | 3.420 | 0.001 | 0.059 | 0.216 |
| 2009 | DCE | 0.303 | 0.045 | 6.710 | 0.000 | 0.215 | 0.392 |
| 2008 | ECHS | 0.126 | 0.073 | 1.720 | 0.085 | -0.017 | 0.270 |
| 2009 | ECHS | 0.470 | 0.067 | 6.990 | 0.000 | 0.338 | 0.602 |

**Outcome Table 42 - Highest HE Degree: Bachelor's (high_degree_bach)**
**Underrepresented Student Population: Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: high_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.019 | 0.037 | -0.510 | 0.613 | -0.090 | 0.053 |
| 2009 | DCE | -0.169 | 0.045 | -3.710 | 0.000 | -0.258 | -0.079 |
| 2008 | ECHS | 0.021 | 0.066 | 0.320 | 0.748 | -0.107 | 0.149 |
| 2009 | ECHS | -0.265 | 0.075 | -3.530 | 0.000 | -0.412 | -0.118 |

## APPENDIX G

## UNDERREPRESENTED STUDENT TABLES: MINORITY (43 - 56)

**Outcome Table 43 - K12 Graduated (k12_graduated)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.310 | 0.023 | 13.770 | 0.000 | 0.266 | 0.355 |
| 2009 | DCE | 0.283 | 0.020 | 13.930 | 0.000 | 0.244 | 0.323 |
| 2008 | ECHS | 0.283 | 0.065 | 4.360 | 0.000 | 0.156 | 0.410 |
| 2009 | ECHS | 0.198 | 0.051 | 3.890 | 0.00 | 0.098 | 0.298 |

**Outcome Table 44 - ACT Composite (act_composite)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.061 | 0.234 | -0.260 | 0.794 | -0.521 | 0.398 |
| 2009 | DCE | 0.591 | 0.201 | 2.950 | 0.003 | 0.198 | 0.984 |
| 2008 | ECHS | 0.429 | 0.438 | 0.980 | 0.33 | -0.431 | 1.288 |
| 2009 | ECHS | 0.948 | 0.648 | 1.460 | 0.143 | -0.321 | 2.218 |

**Outcome Table 45 - ACT Math (act_math)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.269 | 0.279 | 0.970 | 0.334 | -0.277 | 0.815 |
| 2009 | DCE | 0.672 | 0.220 | 3.050 | 0.002 | 0.241 | 1.104 |
| 2008 | ECHS | 0.571 | 0.617 | 0.930 | 0.35 | -0.638 | 1.781 |
| 2009 | ECHS | 1.052 | 0.944 | 1.110 | 0.265 | -0.798 | 2.902 |

**Outcome Table 46 - ACT English (act_english)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.042 | 0.322 | -0.130 | 0.897 | -0.673 | 0.590 |
| 2009 | DCE | 0.379 | 0.285 | 1.330 | 0.183 | -0.179 | 0.938 |
| 2008 | ECHS | 0.673 | 0.731 | 0.92 | 0.357 | -0.759 | 2.105 |
| 2009 | ECHS | 0.914 | 0.857 | 1.070 | 0.286 | -0.765 | 2.593 |

**Outcome Table 47 - ACT Reading (act_reading)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.679 | 0.333 | -2.040 | 0.041 | -1.331 | -0.027 |
| 2009 | DCE | 0.645 | 0.298 | 2.160 | 0.031 | 0.060 | 1.229 |
| 2008 | ECHS | 0.041 | 0.809 | 0.05 | 0.960 | -1.545 | 1.627 |
| 2009 | ECHS | 0.690 | 0.945 | 0.730 | 0.465 | -1.162 | 2.541 |

**Outcome Table 48 - ACT Science (act_science)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.210 | 0.261 | 0.800 | 0.422 | -0.302 | 0.722 |
| 2009 | DCE | 0.722 | 0.231 | 3.120 | 0.002 | 0.269 | 1.176 |
| 2008 | ECHS | 0.735 | 0.666 | 1.10 | 0.270 | -0.570 | 2.039 |
| 2009 | ECHS | 1.431 | 0.735 | 1.950 | 0.052 | -0.009 | 2.871 |

**Outcome Table 49 - Post Secondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.330 | 0.025 | 13.350 | 0.000 | 0.282 | 0.379 |
| 2009 | DCE | 0.360 | 0.022 | 16.610 | 0.000 | 0.318 | 0.403 |
| 2008 | ECHS | 0.322 | 0.08 | 4.190 | 0.000 | 0.172 | 0.473 |
| 2009 | ECHS | 0.291 | 0.063 | 4.610 | 0.000 | 0.167 | 0.415 |

**Outcome Table 50 - Post Secondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.291 | 0.025 | 11.870 | 0.000 | 0.243 | 0.340 |
| 2009 | DCE | 0.281 | 0.022 | 12.560 | 0.000 | 0.237 | 0.325 |
| 2008 | ECHS | 0.309 | 0.07 | 4.470 | 0.000 | 0.174 | 0.445 |
| 2009 | ECHS | 0.247 | 0.061 | 4.020 | 0.000 | 0.127 | 0.368 |

**Outcome Table 51 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.105 | 0.027 | 3.850 | 0.000 | 0.051 | 0.158 |
| 2009 | DCE | 0.052 | 0.023 | 2.250 | 0.025 | 0.007 | 0.097 |
| 2008 | ECHS | 0.254 | 0.08 | 3.110 | 0.002 | 0.094 | 0.414 |
| 2009 | ECHS | 0.407 | 0.062 | 6.540 | 0.000 | 0.285 | 0.529 |

**Outcome Table 52 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.054 | 0.018 | 2.930 | 0.003 | 0.018 | 0.090 |
| 2009 | DCE | 0.007 | 0.015 | 0.490 | 0.625 | -0.021 | 0.036 |
| 2008 | ECHS | 0.250 | 0.08 | 3.250 | 0.001 | 0.099 | 0.401 |
| 2009 | ECHS | 0.352 | 0.066 | 5.330 | 0.000 | 0.222 | 0.481 |

**Outcome Table 53 - Time-to-Completion: Associate's (t2c_assoc)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -240.70 | 101.185 | -2.380 | 0.017 | -439.02 | -42.38 |
| 2009 | DCE | -229.19 | 102.432 | -2.240 | 0.025 | -429.96 | -28.43 |
| 2008 | ECHS | -862.33 | 161.794 | -5.330 | 0.000 | -1179.44 | -545.22 |
| 2009 | ECHS | -909.38 | 69.206 | -13.140 | 0.000 | -1045.03 | -773.74 |

**Outcome Table 54 - Time-to-Completion: Bachelor's (t2c_bach)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -271.73 | 115.374 | -2.360 | 0.019 | -497.86 | -45.61 |
| 2009 | DCE | -239.290 | 83.057 | -2.880 | 0.004 | -402.08 | -76.50 |
| 2008 | ECHS | -436.57 | 207.272 | -2.110 | 0.035 | -842.82 | -30.33 |
| 2009 | ECHS | -454.737 | 183.214 | -2.480 | 0.013 | -813.83 | -95.64 |

**Outcome Table 55 - Highest HE Degree: Associate's (high_degree_assoc)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: high_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.002 | 0.065 | 0.030 | 0.975 | -0.125 | 0.129 |
| 2009 | DCE | 0.279 | 0.080 | 3.480 | 0.001 | 0.122 | 0.436 |
| 2008 | ECHS | 0.188 | 0.106 | 1.760 | 0.078 | -0.021 | 0.396 |
| 2009 | ECHS | 0.271 | 0.093 | 2.920 | 0.004 | 0.089 | 0.453 |

**Outcome Table 56 - Highest HE Degree: Bachelor's (high_degree_bach)**
**Underrepresented Student Population: Minority**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: high_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.053 | 0.060 | 0.890 | 0.374 | -0.064 | 0.170 |
| 2009 | DCE | -0.023 | 0.082 | -0.280 | 0.776 | -0.184 | 0.137 |
| 2008 | ECHS | -0.125 | 0.111 | -1.130 | 0.260 | -0.342 | 0.092 |
| 2009 | ECHS | -0.021 | 0.107 | -0.200 | 0.845 | -0.230 | 0.188 |

# APPENDIX H

# LOW INCOME STUDENT TABLES (57 – 70)

| Outcome Table 57 - K12 Graduated (k12_graduated) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Low Income | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: probit | | | |
| Outcome Model: matching | | | | Outcome Variable: k12_graduated | | | |
| **Cohort** | **Treatment** | **Coefficient** | **AI Robust Standard Error** | ***z* score** | ***P*>\|*z*\|** | **95% Confidence Interval** | |
| 2008 | DCE | 0.309 | 0.014 | 21.870 | 0.000 | 0.282 | 0.337 |
| 2009 | DCE | 0.262 | 0.013 | 20.710 | 0.000 | 0.237 | 0.286 |
| 2008 | ECHS | 0.304 | 0.042 | 7.300 | 0.000 | 0.222 | 0.386 |
| 2009 | ECHS | 0.275 | 0.035 | 7.960 | 0.00 | 0.207 | 0.342 |

| Outcome Table 58 - ACT Composite (act_composite) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Low Income | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: logit | | | |
| Outcome Model: matching | | | | Outcome Variable: act_composite | | | |
| **Cohort** | **Treatment** | **Coefficient** | **AI Robust Standard Error** | ***z* score** | ***P*>\|*z*\|** | **95% Confidence Interval** | |
| 2008 | DCE | 0.371 | 0.129 | 2.880 | 0.004 | 0.118 | 0.623 |
| 2009 | DCE | 0.247 | 0.133 | 1.850 | 0.064 | -0.014 | 0.507 |
| 2008 | ECHS | 0.024 | 0.473 | 0.050 | 0.959 | -0.904 | 0.952 |
| 2009 | ECHS | 0.268 | 0.295 | 0.910 | 0.36 | -0.310 | 0.846 |

| Outcome Table 59 - ACT Math (act_math) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Low Income | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: logit | | | |
| Outcome Model: matching | | | | Outcome Variable: act_math | | | |
| **Cohort** | **Treatment** | **Coefficient** | **AI Robust Standard Error** | ***z* score** | ***P*>\|*z*\|** | **95% Confidence Interval** | |
| 2008 | DCE | 0.668 | 0.164 | 4.070 | 0.000 | 0.346 | 0.990 |
| 2009 | DCE | 0.479 | 0.143 | 3.340 | 0.001 | 0.198 | 0.760 |
| 2008 | ECHS | 0.702 | 0.518 | 1.350 | 0.176 | -0.314 | 1.717 |
| 2009 | ECHS | 0.464 | 0.379 | 1.220 | 0.22 | -0.279 | 1.208 |

| Outcome Table 60 - ACT English (act_english) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: Low Income | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: logit | | | |
| Outcome Model: matching | | | | Outcome Variable: act_english | | | |
| **Cohort** | **Treatment** | **Coefficient** | **AI Robust Standard Error** | ***z* score** | ***P*>\|*z*\|** | **95% Confidence Interval** | |
| 2008 | DCE | 0.608 | 0.189 | 3.220 | 0.001 | 0.238 | 0.979 |
| 2009 | DCE | 0.222 | 0.183 | 1.210 | 0.225 | -0.137 | 0.581 |
| 2008 | ECHS | -0.113 | 0.700 | -0.160 | 0.872 | -1.484 | 1.259 |
| 2009 | ECHS | 0.378 | 0.423 | 0.890 | 0.37 | -0.451 | 1.207 |

**Outcome Table 61 - ACT Reading (act_reading)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.136 | 0.209 | -0.650 | 0.516 | -0.545 | 0.274 |
| 2009 | DCE | -0.129 | 0.194 | -0.670 | 0.505 | -0.509 | 0.251 |
| 2008 | ECHS | -0.847 | 0.638 | -1.330 | 0.185 | -2.098 | 0.404 |
| 2009 | ECHS | -0.324 | 0.451 | -0.720 | 0.47 | -1.209 | 0.560 |

**Outcome Table 62 - ACT Science (act_science)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.371 | 0.166 | 2.230 | 0.026 | 0.045 | 0.697 |
| 2009 | DCE | 0.482 | 0.165 | 2.920 | 0.003 | 0.159 | 0.805 |
| 2008 | ECHS | 0.177 | 0.536 | 0.330 | 0.741 | -0.874 | 1.228 |
| 2009 | ECHS | 0.651 | 0.336 | 1.940 | 0.05 | -0.008 | 1.309 |

**Outcome Table 63 - Post Secondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.315 | 0.016 | 20.070 | 0.000 | 0.284 | 0.346 |
| 2009 | DCE | 0.283 | 0.014 | 20.210 | 0.000 | 0.256 | 0.311 |
| 2008 | ECHS | 0.428 | 0.046 | 9.290 | 0.000 | 0.338 | 0.519 |
| 2009 | ECHS | 0.311 | 0.045 | 6.910 | 0.00 | 0.223 | 0.399 |

**Outcome Table 64 - Post Secondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.295 | 0.016 | 18.790 | 0.000 | 0.264 | 0.326 |
| 2009 | DCE | 0.261 | 0.014 | 18.780 | 0.000 | 0.234 | 0.288 |
| 2008 | ECHS | 0.380 | 0.046 | 8.350 | 0.000 | 0.291 | 0.470 |
| 2009 | ECHS | 0.257 | 0.039 | 6.640 | 0.00 | 0.181 | 0.332 |

**Outcome Table 65 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.148 | 0.016 | 8.990 | 0.000 | 0.115 | 0.180 |
| 2009 | DCE | 0.098 | 0.014 | 6.860 | 0.000 | 0.070 | 0.126 |
| 2008 | ECHS | 0.404 | 0.050 | 8.020 | 0.000 | 0.305 | 0.503 |
| 2009 | ECHS | 0.473 | 0.043 | 10.960 | 0.00 | 0.389 | 0.558 |

**Outcome Table 66 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.045 | 0.014 | 3.270 | 0.001 | 0.018 | 0.072 |
| 2009 | DCE | 0.024 | 0.012 | 1.910 | 0.056 | -0.001 | 0.048 |
| 2008 | ECHS | 0.328 | 0.046 | 7.070 | 0.000 | 0.237 | 0.418 |
| 2009 | ECHS | 0.394 | 0.040 | 9.840 | 0.00 | 0.315 | 0.472 |

**Outcome Table 67 - Time-to-Completion: Associate’s (t2c_assoc)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -340.14 | 68.222 | -4.990 | 0.000 | -473.85 | -206.43 |
| 2009 | DCE | -258.19 | 47.043 | -5.490 | 0.000 | -350.39 | -165.98 |
| 2008 | ECHS | -907.55 | 90.010 | -10.080 | 0.000 | -1083.97 | -731.14 |
| 2009 | ECHS | -827.42 | 55.787 | -14.830 | 0.00 | -936.76 | -718.08 |

**Outcome Table 68 - Time-to-Completion: Bachelor’s (t2c_bach)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -209.77 | 69.791 | -3.010 | 0.003 | -346.56 | -72.98 |
| 2009 | DCE | -126.89 | 69.996 | -1.810 | 0.070 | -264.08 | 10.30 |
| 2008 | ECHS | -418.26 | 115.410 | -3.620 | 0.000 | -644.46 | -192.06 |
| 2009 | ECHS | -252.85 | 86.683 | -2.920 | 0.00 | -422.74 | -82.95 |

**Outcome Table 69 - Highest HE Degree: Associate's (high_degree_assoc)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: high_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.130 | 0.046 | 2.820 | 0.005 | 0.040 | 0.220 |
| 2009 | DCE | 0.127 | 0.048 | 2.650 | 0.008 | 0.033 | 0.222 |
| 2008 | ECHS | 0.110 | 0.078 | 1.410 | 0.159 | -0.043 | 0.264 |
| 2009 | ECHS | 0.050 | 0.072 | 0.690 | 0.488 | -0.091 | 0.191 |

**Outcome Table 70 - Highest HE Degree: Bachelor's (high_degree_bach)**
**Underrepresented Student Population: Low Income**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: high_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.020 | 0.042 | 0.480 | 0.631 | -0.062 | 0.103 |
| 2009 | DCE | 0.067 | 0.038 | 1.750 | 0.080 | -0.008 | 0.143 |
| 2008 | ECHS | 0.041 | 0.072 | 0.560 | 0.573 | -0.101 | 0.182 |
| 2009 | ECHS | 0.121 | 0.055 | 2.200 | 0.028 | 0.013 | 0.230 |

# APPENDIX I

# ENGLISH LANGUAGE LEARNER STUDENT TABLES (71 - 84)

**Outcome Table 71 - K12 Graduated (k12_graduated)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.332 | 0.031 | 10.700 | 0.000 | 0.272 | 0.393 |
| 2009 | DCE | 0.248 | 0.024 | 10.280 | 0.000 | 0.201 | 0.295 |
| 2008 | ECHS | 0.348 | 0.089 | 3.910 | 0.000 | 0.173 | 0.522 |
| 2009 | ECHS | 0.208 | 0.064 | 3.230 | 0.00 | 0.082 | 0.333 |

**Outcome Table 72 - ACT Composite (act_composite)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.616 | 0.288 | 2.140 | 0.033 | 0.051 | 1.181 |
| 2009 | DCE | 0.077 | 0.295 | 0.260 | 0.793 | -0.501 | 0.656 |
| 2008 | ECHS | 1.029 | 0.784 | 1.310 | 0.189 | -0.507 | 2.565 |
| 2009 | ECHS | 0.528 | 0.754 | 0.700 | 0.48 | -0.950 | 2.006 |

**Outcome Table 73 - ACT Math (act_math)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.893 | 0.359 | 2.480 | 0.013 | 0.188 | 1.598 |
| 2009 | DCE | -0.237 | 0.346 | -0.690 | 0.493 | -0.915 | 0.441 |
| 2008 | ECHS | 1.029 | 0.903 | 1.140 | 0.254 | -0.740 | 2.799 |
| 2009 | ECHS | 1.278 | 0.853 | 1.500 | 0.13 | -0.393 | 2.949 |

**Outcome Table 74 - ACT English (act_english)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.781 | 0.414 | 1.890 | 0.059 | -0.030 | 1.593 |
| 2009 | DCE | 0.003 | 0.406 | 0.010 | 0.994 | -0.793 | 0.798 |
| 2008 | ECHS | 1.647 | 0.513 | 3.210 | 0.001 | 0.642 | 2.652 |
| 2009 | ECHS | 0.278 | 0.984 | 0.280 | 0.78 | -1.650 | 2.205 |

**Outcome Table 75 - ACT Reading (act_reading)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.129 | 0.413 | 0.310 | 0.755 | -0.681 | 0.939 |
| 2009 | DCE | 0.210 | 0.378 | 0.560 | 0.579 | -0.531 | 0.950 |
| 2008 | ECHS | 0.500 | 0.759 | 0.660 | 0.510 | -0.988 | 1.988 |
| 2009 | ECHS | 0.639 | 1.002 | 0.640 | 0.52 | -1.326 | 2.603 |

**Outcome Table 76 - ACT Science (act_science)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.733 | 0.327 | 2.240 | 0.025 | 0.091 | 1.374 |
| 2009 | DCE | 0.238 | 0.368 | 0.650 | 0.518 | -0.483 | 0.959 |
| 2008 | ECHS | 1.676 | 0.510 | 3.290 | 0.001 | 0.677 | 2.676 |
| 2009 | ECHS | 0.500 | 0.871 | 0.57 | 0.566 | -1.207 | 2.207 |

**Outcome Table 77 - Postsecondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.313 | 0.033 | 9.520 | 0.000 | 0.249 | 0.378 |
| 2009 | DCE | 0.334 | 0.028 | 11.940 | 0.000 | 0.279 | 0.389 |
| 2008 | ECHS | 0.435 | 0.098 | 4.420 | 0.000 | 0.242 | 0.628 |
| 2009 | ECHS | 0.358 | 0.093 | 3.85 | 0.000 | 0.176 | 0.541 |

**Outcome Table 78 - Postsecondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.304 | 0.031 | 9.690 | 0.000 | 0.243 | 0.366 |
| 2009 | DCE | 0.286 | 0.027 | 10.520 | 0.000 | 0.233 | 0.340 |
| 2008 | ECHS | 0.435 | 0.098 | 4.440 | 0.000 | 0.243 | 0.627 |
| 2009 | ECHS | 0.208 | 0.077 | 2.70 | 0.007 | 0.057 | 0.358 |

**Outcome Table 79 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.099 | 0.033 | 2.950 | 0.003 | 0.033 | 0.164 |
| 2009 | DCE | 0.058 | 0.030 | 1.960 | 0.050 | 0.000 | 0.116 |
| 2008 | ECHS | 0.220 | 0.097 | 2.270 | 0.023 | 0.030 | 0.409 |
| 2009 | ECHS | 0.396 | 0.079 | 5.03 | 0.000 | 0.242 | 0.550 |

**Outcome Table 80 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.050 | 0.028 | 1.800 | 0.072 | -0.005 | 0.105 |
| 2009 | DCE | 0.030 | 0.020 | 1.510 | 0.132 | -0.009 | 0.068 |
| 2008 | ECHS | 0.196 | 0.080 | 2.450 | 0.014 | 0.039 | 0.352 |
| 2009 | ECHS | 0.453 | 0.069 | 6.61 | 0.000 | 0.318 | 0.587 |

**Outcome Table 81 - Time-to-Completion: Associate's (t2c_assoc)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -313.50 | 89.272 | -3.510 | 0.000 | -488.47 | -138.53 |
| 2009 | DCE | -144.24 | 75.717 | -1.900 | 0.057 | -292.64 | 4.16 |
| 2008 | ECHS | -758.19 | 121.960 | -6.220 | 0.000 | -997.22 | -519.15 |
| 2009 | ECHS | -710.680 | 212.777 | -3.34 | 0.001 | -1127.71 | -293.65 |

**Outcome Table 82 - Time-to-Completion: Bachelor's (t2c_bach)**
**Underrepresented Student Population: English Language Learner**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -149.82 | 118.156 | -1.270 | 0.205 | -381.40 | 81.76 |
| 2009 | DCE | 112.11 | 85.665 | 1.310 | 0.191 | -55.79 | 280.01 |
| 2008 | ECHS | -301.50 | 238.904 | -1.260 | 0.207 | -769.74 | 166.74 |
| 2009 | ECHS | -160.429 | 31.32234 | -5.12 | 0.000 | -221.82 | -99.04 |

| Outcome Table 83 - Highest HE Degree: Associate's (high_degree_assoc) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: English Language Learner | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: probit | | | |
| Outcome Model: matching | | | | Outcome Variable: high_degree_assoc | | | |
| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
| 2008 | DCE | -0.128 | 0.093 | -1.370 | 0.172 | -0.311 | 0.055 |
| 2009 | DCE | 0.295 | 0.072 | 4.110 | 0.000 | 0.154 | 0.435 |
| 2008 | ECHS | -0.053 | 0.074 | -0.720 | 0.474 | -0.197 | 0.091 |
| 2009 | ECHS | 0.226 | 0.116 | 1.950 | 0.051 | -0.001 | 0.453 |

| Outcome Table 84 - Highest HE Degree: Bachelor's (high_degree_bach) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Underrepresented Student Population: English Language Learner | | | | | | | |
| Treatment Effects Estimation: ATET | | | | Treatment Model: probit | | | |
| Outcome Model: matching | | | | Outcome Variable: high_degree_bach | | | |
| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
| 2008 | DCE | 0.234 | 0.078 | 3.020 | 0.003 | 0.082 | 0.3860 |
| 2009 | DCE | 0.014 | 0.060 | 0.230 | 0.820 | -0.105 | 0.1320 |
| 2008 | ECHS | 0.368 | 0.095 | 3.880 | 0.000 | 0.182 | 0.555 |
| 2009 | ECHS | 0.065 | 0.118 | 0.550 | 0.585 | -0.167 | 0.296 |

# APPENDIX J

# MINORITY MALE STUDENT TABLES (85 - 98)

**Outcome Table 85 - K12 Graduated (k12_graduated)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.324 | 0.033 | 9.730 | 0.000 | 0.258 | 0.389 |
| 2009 | DCE | 0.332 | 0.029 | 11.480 | 0.000 | 0.275 | 0.388 |
| 2008 | ECHS | 0.500 | 0.106 | 4.700 | 0.000 | 0.292 | 0.708 |
| 2009 | ECHS | 0.233 | 0.087 | 2.670 | 0.01 | 0.062 | 0.405 |

**Outcome Table 76 - ACT Composite (act_composite)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.421 | 0.302 | 1.390 | 0.164 | -0.172 | 1.013 |
| 2009 | DCE | 0.439 | 0.315 | 1.400 | 0.163 | -0.178 | 1.056 |
| 2008 | ECHS | 0.389 | 1.075 | 0.360 | 0.717 | -1.718 | 2.495 |
| 2009 | ECHS | 0.643 | 1.483 | 0.430 | 0.67 | -2.265 | 3.550 |

**Outcome Table 87 - ACT Math (act_math)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.525 | 0.363 | 1.450 | 0.148 | -0.186 | 1.237 |
| 2009 | DCE | 0.785 | 0.341 | 2.300 | 0.021 | 0.117 | 1.453 |
| 2008 | ECHS | 1.556 | 1.018 | 1.530 | 0.126 | -0.439 | 3.550 |
| 2009 | ECHS | 1.107 | 1.571 | 0.700 | 0.48 | -1.973 | 4.187 |

**Outcome Table 88 - ACT English (act_english)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.366 | 0.421 | 0.870 | 0.385 | -0.459 | 1.192 |
| 2009 | DCE | 0.505 | 0.400 | 1.260 | 0.207 | -0.280 | 1.290 |
| 2008 | ECHS | 1.722 | 1.186 | 1.450 | 0.146 | -0.602 | 4.046 |
| 2009 | ECHS | -0.107 | 1.316 | -0.080 | 0.94 | -2.686 | 2.471 |

**Outcome Table 89 - ACT Reading (act_reading)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.372 | 0.449 | 0.830 | 0.407 | -0.508 | 1.252 |
| 2009 | DCE | 0.285 | 0.469 | 0.610 | 0.543 | -0.633 | 1.203 |
| 2008 | ECHS | -1.056 | 1.736 | -0.610 | 0.543 | -4.457 | 2.346 |
| 2009 | ECHS | 1.929 | 1.806 | 1.070 | 0.286 | -1.611 | 5.468 |

**Outcome Table 90 - ACT Science (act_science)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.678 | 0.385 | 1.760 | 0.079 | -0.078 | 1.433 |
| 2009 | DCE | 0.053 | 0.385 | 0.140 | 0.890 | -0.702 | 0.808 |
| 2008 | ECHS | -0.389 | 0.090 | -4.310 | 0.000 | -0.566 | -0.212 |
| 2009 | ECHS | 0.679 | 1.664 | 0.410 | 0.683 | -2.582 | 3.939 |

**Outcome Table 91 - Postsecondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.333 | 0.037 | 8.940 | 0.000 | 0.260 | 0.406 |
| 2009 | DCE | 0.331 | 0.031 | 10.540 | 0.000 | 0.269 | 0.392 |
| 2008 | ECHS | 0.393 | 0.094 | 4.190 | 0.000 | 0.209 | 0.577 |
| 2009 | ECHS | 0.367 | 0.084 | 4.380 | 0.000 | 0.203 | 0.531 |

**Outcome Table 92 - Postsecondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.279 | 0.037 | 7.610 | 0.000 | 0.207 | 0.350 |
| 2009 | DCE | 0.270 | 0.031 | 8.690 | 0.000 | 0.209 | 0.331 |
| 2008 | ECHS | 0.357 | 0.122 | 2.920 | 0.003 | 0.118 | 0.597 |
| 2009 | ECHS | 0.333 | 0.084 | 3.960 | 0.000 | 0.168 | 0.498 |

**Outcome Table 93 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.122 | 0.032 | 3.850 | 0.000 | 0.060 | 0.184 |
| 2009 | DCE | 0.067 | 0.024 | 2.790 | 0.005 | 0.020 | 0.114 |
| 2008 | ECHS | 0.391 | 0.116 | 3.370 | 0.001 | 0.164 | 0.619 |
| 2009 | ECHS | 0.500 | 0.092 | 5.420 | 0.000 | 0.319 | 0.681 |

**Outcome Table 94 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.029 | 0.024 | 1.240 | 0.215 | -0.017 | 0.075 |
| 2009 | DCE | 0.015 | 0.024 | 0.600 | 0.548 | -0.033 | 0.062 |
| 2008 | ECHS | 0.321 | 0.096 | 3.330 | 0.001 | 0.132 | 0.510 |
| 2009 | ECHS | 0.433 | 0.091 | 4.740 | 0.000 | 0.254 | 0.613 |

**Outcome Table 95 - Time-to-Completion: Associate's (t2c_assoc)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -194.79 | 111.476 | -1.750 | 0.081 | -413.28 | 23.70 |
| 2009 | DCE | overlap assumption violated | | | | | |
| 2008 | ECHS | -762.40 | 133.427 | -5.710 | 0.000 | -1023.91 | -500.89 |
| 2009 | ECHS | overlap assumption violated | | | | | |

**Outcome Table 96 - Time-to-Completion: Bachelor's (t2c_bach)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -392.21 | 137.498 | -2.850 | 0.004 | -661.70 | -122.72 |
| 2009 | DCE | overlap assumption violated | | | | | |
| 2008 | ECHS | -117.50 | 131.385 | -0.890 | 0.371 | -375.01 | 140.01 |
| 2009 | ECHS | overlap assumption violated | | | | | |

**Outcome Table 97 - Highest HE Degree: Associate's (high_degree_assoc)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: high_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.190 | 0.100 | 1.910 | 0.057 | -0.005 | 0.385 |
| 2009 | DCE | 0.150 | 0.113 | 1.330 | 0.185 | -0.072 | 0.372 |
| 2008 | ECHS | 0.364 | 0.151 | 2.410 | 0.016 | 0.068 | 0.660 |
| 2009 | ECHS | 0.200 | 0.216 | 0.930 | 0.354 | -0.223 | 0.623 |

**Outcome Table 98 - Highest HE Degree: Bachelor's (high_degree_bach)**
**Underrepresented Student Population: Minority Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: high_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.051 | 0.103 | 0.490 | 0.622 | -0.151 | 0.252 |
| 2009 | DCE | 0.050 | 0.073 | 0.680 | 0.495 | -0.094 | 0.194 |
| 2008 | ECHS | 0.000 | 0.147 | 0.000 | 1.000 | -0.288 | 0.288 |
| 2009 | ECHS | -0.133 | 0.197 | -0.680 | 0.499 | -0.520 | 0.253 |

## APPENDIX K

## MINORITY FEMALE STUDENT TABLES (99 – 112)

**Outcome Table 99 - K12 Graduated (k12_graduated)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.304 | 0.032 | 9.530 | 0.000 | 0.242 | 0.367 |
| 2009 | DCE | 0.258 | 0.026 | 9.920 | 0.000 | 0.207 | 0.309 |
| 2008 | ECHS | 0.208 | 0.080 | 2.620 | 0.009 | 0.052 | 0.364 |
| 2009 | ECHS | 0.262 | 0.061 | 4.310 | 0.00 | 0.143 | 0.381 |

**Outcome Table 100 - ACT Composite (act_composite)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.429 | 0.321 | 1.340 | 0.182 | -0.200 | 1.059 |
| 2009 | DCE | 0.282 | 0.317 | 0.890 | 0.375 | -0.340 | 0.904 |
| 2008 | ECHS | 0.484 | 0.945 | 0.510 | 0.609 | -1.369 | 2.337 |
| 2009 | ECHS | -0.045 | 0.529 | -0.090 | 0.93 | -1.083 | 0.992 |

**Outcome Table 101 - ACT Math (act_math)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 1.001 | 0.388 | 2.580 | 0.010 | 0.241 | 1.761 |
| 2009 | DCE | -0.153 | 0.331 | -0.460 | 0.643 | -0.801 | 0.495 |
| 2008 | ECHS | 0.613 | 0.732 | 0.840 | 0.402 | -0.821 | 2.047 |
| 2009 | ECHS | 0.489 | 0.624 | 0.780 | 0.43 | -0.735 | 1.712 |

**Outcome Table 102 - ACT English (act_english)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.504 | 0.463 | 1.090 | 0.277 | -0.405 | 1.412 |
| 2009 | DCE | 0.189 | 0.421 | 0.450 | 0.653 | -0.635 | 1.013 |
| 2008 | ECHS | 1.548 | 1.381 | 1.120 | 0.262 | -1.158 | 4.255 |
| 2009 | ECHS | -0.045 | 0.863 | -0.050 | 0.96 | -1.738 | 1.647 |

**Outcome Table 103 - ACT Reading (act_reading)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.555 | 0.431 | -1.290 | 0.197 | -1.400 | 0.289 |
| 2009 | DCE | 0.824 | 0.393 | 2.100 | 0.036 | 0.054 | 1.594 |
| 2008 | ECHS | -0.145 | 1.284 | -0.110 | 0.910 | -2.662 | 2.372 |
| 2009 | ECHS | -0.750 | 0.729 | -1.030 | 0.303 | -2.178 | 0.678 |

**Outcome Table 104 - ACT Science (act_science)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.572 | 0.365 | 1.570 | 0.117 | -0.143 | 1.287 |
| 2009 | DCE | 0.287 | 0.354 | 0.810 | 0.417 | -0.406 | 0.981 |
| 2008 | ECHS | 0.339 | 1.062 | 0.320 | 0.750 | -1.742 | 2.419 |
| 2009 | ECHS | 0.205 | 0.574 | 0.360 | 0.722 | -0.921 | 1.330 |

**Outcome Table 105 - Postsecondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.334 | 0.037 | 9.140 | 0.000 | 0.262 | 0.405 |
| 2009 | DCE | 0.349 | 0.031 | 11.210 | 0.000 | 0.288 | 0.410 |
| 2008 | ECHS | 0.375 | 0.091 | 4.120 | 0.000 | 0.197 | 0.553 |
| 2009 | ECHS | 0.426 | 0.083 | 5.140 | 0.000 | 0.264 | 0.589 |

**Outcome Table 106 - Postsecondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.274 | 0.034 | 8.090 | 0.000 | 0.208 | 0.341 |
| 2009 | DCE | 0.293 | 0.030 | 9.800 | 0.000 | 0.235 | 0.352 |
| 2008 | ECHS | 0.375 | 0.080 | 4.670 | 0.000 | 0.217 | 0.533 |
| 2009 | ECHS | 0.361 | 0.081 | 4.430 | 0.000 | 0.201 | 0.520 |

**Outcome Table 107 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.124 | 0.035 | 3.490 | 0.000 | 0.054 | 0.193 |
| 2009 | DCE | 0.068 | 0.038 | 1.780 | 0.076 | -0.007 | 0.143 |
| 2008 | ECHS | 0.391 | 0.116 | 3.370 | 0.001 | 0.164 | 0.619 |
| 2009 | ECHS | 0.418 | 0.080 | 5.210 | 0.000 | 0.261 | 0.576 |

**Outcome Table 108 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** — **Treatment Model: probit**
**Outcome Model: matching** — **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.084 | 0.032 | 2.600 | 0.009 | 0.021 | 0.148 |
| 2009 | DCE | -0.015 | 0.030 | -0.520 | 0.605 | -0.073 | 0.043 |
| 2008 | ECHS | 0.167 | 0.125 | 1.330 | 0.184 | -0.079 | 0.412 |
| 2009 | ECHS | 0.262 | 0.087 | 3.020 | 0.003 | 0.092 | 0.433 |

**Outcome Table 109 - Time-to-Completion: Associate's (t2c_assoc)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -149.95 | 94.473 | -1.590 | 0.112 | -335.11 | 35.21 |
| 2009 | DCE | -221.91 | 72.092 | -3.080 | 0.002 | -363.20 | -80.61 |
| 2008 | ECHS | -803.18 | 156.007 | -5.150 | 0.000 | -1108.94 | -497.4 |
| 2009 | ECHS | -938.96 | 88.629 | -10.590 | 0.000 | -1112.67 | -765.1 |

**Outcome Table 110 - Time-to-Completion: Bachelor's (t2c_bach)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** — **Treatment Model: logit**
**Outcome Model: matching** — **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -170.08 | 114.650 | -1.480 | 0.138 | -394.79 | 54.63 |
| 2009 | DCE | -163.38 | 123.616 | -1.320 | 0.186 | -405.66 | 78.91 |
| 2008 | ECHS | -19.75 | 240.056 | -0.080 | 0.934 | -490.25 | 450.75 |
| 2009 | ECHS | -126.59 | 151.423 | -0.840 | 0.403 | -423.37 | 170.20 |

**Outcome Table 111 - High HE Degree: Associate's (high_he_degree_assoc)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: high_he_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.06 | 0.087 | 0.700 | 0.487 | -0.11 | 0.23 |
| 2009 | DCE | 0.34 | 0.083 | 4.130 | 0.000 | 0.18 | 0.50 |
| 2008 | ECHS | 0.33 | 0.190 | 1.750 | 0.080 | -0.04 | 0.71 |
| 2009 | ECHS | 0.12 | 0.153 | 0.790 | 0.429 | -0.18 | 0.42 |

**Outcome Table 112 - High HE Degree: Bachelor's (high_he_degree_bach)**
**Underrepresented Student Population: Minority Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: high_he_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.06 | 0.078 | 0.770 | 0.442 | -0.09 | 0.21 |
| 2009 | DCE | -0.12 | 0.081 | -1.500 | 0.132 | -0.28 | 0.04 |
| 2008 | ECHS | -0.29 | 0.187 | -1.530 | 0.126 | -0.65 | 0.08 |
| 2009 | ECHS | -0.09 | 0.163 | -0.560 | 0.577 | -0.41 | 0.23 |

APPENDIX L

LOW INCOME MALE STUDENT POPULATION (113 – 126)

**Outcome Table 113 - K12 Graduated (k12_graduated)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: k12_graduated**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.318 | 0.022 | 14.690 | 0.000 | 0.276 | 0.360 |
| 2009 | DCE | 0.299 | 0.019 | 16.110 | 0.000 | 0.263 | 0.336 |
| 2008 | ECHS | 0.359 | 0.072 | 5.000 | 0.000 | 0.218 | 0.499 |
| 2009 | ECHS | 0.351 | 0.058 | 6.020 | 0.00 | 0.237 | 0.466 |

**Outcome Table 114 - ACT Composite (act_composite)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.721 | 0.215 | 3.360 | 0.001 | 0.300 | 1.142 |
| 2009 | DCE | 0.229 | 0.185 | 1.240 | 0.217 | -0.134 | 0.592 |
| 2008 | ECHS | 0.234 | 0.677 | 0.350 | 0.730 | -1.094 | 1.562 |
| 2009 | ECHS | 1.255 | 0.575 | 2.180 | 0.03 | 0.128 | 2.381 |

**Outcome Table 115 - ACT Math (act_math)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 1.011 | 0.276 | 3.660 | 0.000 | 0.470 | 1.552 |
| 2009 | DCE | 0.517 | 0.209 | 2.470 | 0.013 | 0.107 | 0.926 |
| 2008 | ECHS | 0.894 | 0.776 | 1.150 | 0.250 | -0.628 | 2.415 |
| 2009 | ECHS | 2.028 | 0.657 | 3.090 | 0.00 | 0.740 | 3.317 |

**Outcome Table 117 - ACT Reading (act_reading)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.581 | 0.363 | 1.600 | 0.109 | -0.129 | 1.292 |
| 2009 | DCE | 0.048 | 0.283 | 0.170 | 0.865 | -0.506 | 0.602 |
| 2008 | ECHS | -0.723 | 0.937 | -0.770 | 0.440 | -2.561 | 1.114 |
| 2009 | ECHS | 0.217 | 0.980 | 0.220 | 0.825 | -1.705 | 2.139 |

**Outcome Table 118 - ACT Science (act_science)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.718 | 0.254 | 2.830 | 0.005 | 0.221 | 1.216 |
| 2009 | DCE | 0.230 | 0.222 | 1.040 | 0.299 | -0.204 | 0.665 |
| 2008 | ECHS | 1.149 | 0.770 | 1.490 | 0.136 | -0.360 | 2.658 |
| 2009 | ECHS | 1.123 | 0.760 | 1.480 | 0.140 | -0.367 | 2.612 |

**Outcome Table 119 - Postsecondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.260 | 0.024 | 10.650 | 0.000 | 0.212 | 0.308 |
| 2009 | DCE | 0.304 | 0.022 | 13.990 | 0.000 | 0.261 | 0.347 |
| 2008 | ECHS | 0.250 | 0.093 | 2.690 | 0.007 | 0.068 | 0.432 |
| 2009 | ECHS | 0.384 | 0.067 | 5.730 | 0.000 | 0.252 | 0.515 |

**Outcome Table 120 - Postsecondary Higher Education Enrollment (post_enroll_all)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.273 | 0.023 | 11.670 | 0.000 | 0.227 | 0.319 |
| 2009 | DCE | 0.283 | 0.021 | 13.560 | 0.000 | 0.242 | 0.324 |
| 2008 | ECHS | 0.290 | 0.080 | 3.650 | 0.000 | 0.134 | 0.446 |
| 2009 | ECHS | 0.384 | 0.065 | 5.880 | 0.000 | 0.256 | 0.511 |

**Outcome Table 121 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.104 | 0.019 | 5.390 | 0.000 | 0.066 | 0.142 |
| 2009 | DCE | 0.078 | 0.017 | 4.610 | 0.000 | 0.045 | 0.110 |
| 2008 | ECHS | 0.386 | 0.075 | 5.150 | 0.000 | 0.239 | 0.533 |
| 2009 | ECHS | 0.526 | 0.059 | 8.990 | 0.000 | 0.412 | 0.641 |

**Outcome Table 122 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.037 | 0.013 | 2.780 | 0.005 | 0.011 | 0.064 |
| 2009 | DCE | 0.021 | 0.013 | 1.640 | 0.101 | -0.004 | 0.047 |
| 2008 | ECHS | 0.323 | 0.070 | 4.590 | 0.000 | 0.185 | 0.460 |
| 2009 | ECHS | 0.419 | 0.057 | 7.310 | 0.000 | 0.307 | 0.532 |

**Outcome Table 123 - Time-to-Completion: Associate's (t2c_assoc)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -227.52 | 114.240 | -1.990 | 0.046 | -451.4 | -3.61 |
| 2009 | DCE | -325.28 | 109.446 | -2.970 | 0.003 | -539.7 | -110.78 |
| 2008 | ECHS | -1022.43 | 116.151 | -8.800 | 0.000 | -1250. | -794.78 |
| 2009 | ECHS | -961.40 | 126.457 | -7.600 | 0.000 | -1209. | -713.55 |

**Outcome Table 124 - Time-to-Completion: Bachelor's (t2c_bach)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -78.71 | 93.396 | -0.840 | 0.399 | -261.7 | 104.34 |
| 2009 | DCE | -87.59 | 115.526 | -0.760 | 0.448 | -314.0 | 138.83 |
| 2008 | ECHS | -357.71 | 381.187 | -0.940 | 0.348 | -1104. | 389.40 |
| 2009 | ECHS | -361.29 | 25.943 | -13.930 | 0.000 | -412.1 | -310.44 |

**Outcome Table 125 - High HE Degree: Associate's (high_he_degree_assoc)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: high_he_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.35 | 0.076 | 4.530 | 0.000 | 0.20 | 0.49 |
| 2009 | DCE | 0.30 | 0.095 | 3.100 | 0.002 | 0.11 | 0.48 |
| 2008 | ECHS | 0.36 | 0.131 | 2.730 | 0.006 | 0.10 | 0.61 |
| 2009 | ECHS | 0.17 | 0.122 | 1.390 | 0.164 | -0.07 | 0.41 |

**Outcome Table 126 - High HE Degree: Bachelor's (high_he_degree_bach)**
**Underrepresented Student Population: Low Income Male**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: high_he_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.07 | 0.079 | -0.880 | 0.377 | -0.23 | 0.09 |
| 2009 | DCE | -0.02 | 0.067 | -0.330 | 0.739 | -0.15 | 0.11 |
| 2008 | ECHS | -0.04 | 0.125 | -0.290 | 0.776 | -0.28 | 0.21 |
| 2009 | ECHS | -0.04 | 0.095 | -0.450 | 0.653 | -0.23 | 0.14 |

# APPENDIX M

## LOW INCOME FEMALE STUDENT TABLES (127 – 140)

**Outcome Table 127 - K12 Graduation (k12_graduation)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: k12_graduation**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.29 | 0.020 | 14.890 | 0.000 | 0.25 | 0.33 |
| 2009 | DCE | 0.29 | 0.017 | 17.150 | 0.000 | 0.26 | 0.32 |
| 2008 | ECHS | 0.36 | 0.052 | 6.820 | 0.000 | 0.25 | 0.46 |
| 2009 | ECHS | 0.25 | 0.039 | 6.340 | 0.000 | 0.17 | 0.33 |

**Outcome Table 128 - ACT Composite (act_composite)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_composite**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.33 | 0.173 | 1.890 | 0.059 | -0.01 | 0.67 |
| 2009 | DCE | 0.48 | 0.146 | 3.270 | 0.001 | 0.19 | 0.76 |
| 2008 | ECHS | 0.82 | 0.434 | 1.890 | 0.059 | -0.03 | 1.67 |
| 2009 | ECHS | 0.70 | 0.295 | 2.370 | 0.018 | 0.12 | 1.28 |

**Outcome Table 129 - ACT Math (act_math)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_math**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.581 | 0.186 | 3.130 | 0.002 | 0.217 | 0.945 |
| 2009 | DCE | 0.558 | 0.160 | 3.500 | 0.000 | 0.245 | 0.871 |
| 2008 | ECHS | 1.104 | 0.450 | 2.450 | 0.014 | 0.222 | 1.986 |
| 2009 | ECHS | 0.450 | 0.394 | 1.140 | 0.25 | -0.322 | 1.222 |

**Outcome Table 130 - ACT English (act_english)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: act_english**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.502 | 0.256 | 1.960 | 0.050 | 0.001 | 1.003 |
| 2009 | DCE | 0.463 | 0.223 | 2.080 | 0.037 | 0.027 | 0.900 |
| 2008 | ECHS | 1.503 | 0.601 | 2.500 | 0.012 | 0.325 | 2.682 |
| 2009 | ECHS | 1.209 | 0.430 | 2.810 | 0.01 | 0.366 | 2.052 |

**Outcome Table 131 - ACT Reading (act_reading)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_reading**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -0.309 | 0.261 | -1.180 | 0.237 | -0.821 | 0.203 |
| 2009 | DCE | 0.213 | 0.223 | 0.960 | 0.339 | -0.223 | 0.649 |
| 2008 | ECHS | 0.127 | 0.769 | 0.160 | 0.869 | -1.381 | 1.635 |
| 2009 | ECHS | 0.287 | 0.470 | 0.610 | 0.542 | -0.635 | 1.209 |

**Outcome Table 132 - ACT Science (act_science)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** **Treatment Model: logit**
**Outcome Model: matching** **Outcome Variable: act_science**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.464 | 0.214 | 2.170 | 0.030 | 0.045 | 0.883 |
| 2009 | DCE | 0.728 | 0.171 | 4.260 | 0.000 | 0.393 | 1.062 |
| 2008 | ECHS | 0.432 | 0.562 | 0.770 | 0.442 | -0.670 | 1.534 |
| 2009 | ECHS | 0.748 | 0.348 | 2.150 | 0.031 | 0.067 | 1.429 |

**Outcome Table 133 - Postsecondary Higher Education Enrollment (post_enroll)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.330 | 0.023 | 14.560 | 0.000 | 0.286 | 0.375 |
| 2009 | DCE | 0.310 | 0.020 | 15.580 | 0.000 | 0.271 | 0.349 |
| 2008 | ECHS | 0.455 | 0.062 | 7.380 | 0.000 | 0.334 | 0.576 |
| 2009 | ECHS | 0.313 | 0.051 | 6.130 | 0.000 | 0.213 | 0.413 |

**Outcome Table 134 - Postsecondary Higher Education Enrollment - All (post_enroll_all)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** **Treatment Model: probit**
**Outcome Model: matching** **Outcome Variable: post_enroll_all**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.330 | 0.023 | 14.560 | 0.000 | 0.286 | 0.375 |
| 2009 | DCE | 0.286 | 0.019 | 14.920 | 0.000 | 0.248 | 0.323 |
| 2008 | ECHS | 0.344 | 0.062 | 5.570 | 0.000 | 0.223 | 0.465 |
| 2009 | ECHS | 0.250 | 0.044 | 5.650 | 0.000 | 0.163 | 0.337 |

**Outcome Table 135 - Utah Higher Education Graduate (he_grad)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: he_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.130 | 0.027 | 4.850 | 0.000 | 0.077 | 0.182 |
| 2009 | DCE | 0.103 | 0.022 | 4.750 | 0.000 | 0.061 | 0.146 |
| 2008 | ECHS | 0.392 | 0.069 | 5.700 | 0.000 | 0.257 | 0.527 |
| 2009 | ECHS | 0.396 | 0.057 | 7.000 | 0.000 | 0.285 | 0.507 |

**Outcome Table 136 - Utah Higher Education Graduate (ushe_grad)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: probit**
**Outcome Model: matching** | **Outcome Variable: ushe_grad**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.073 | 0.021 | 3.430 | 0.001 | 0.031 | 0.115 |
| 2009 | DCE | 0.017 | 0.017 | 0.960 | 0.337 | -0.017 | 0.051 |
| 2008 | ECHS | 0.348 | 0.056 | 6.170 | 0.000 | 0.238 | 0.459 |
| 2009 | ECHS | 0.380 | 0.053 | 7.160 | 0.000 | 0.276 | 0.483 |

**Outcome Table 137 - Time-to-Completion: Associate's (t2c_assoc)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -247.67 | 54.982 | -4.500 | 0.000 | -355.44 | -139. |
| 2009 | DCE | -264.20 | 40.239 | -6.570 | 0.000 | -343.07 | -185. |
| 2008 | ECHS | -653.76 | 86.819 | -7.530 | 0.000 | -823.92 | -483. |
| 2009 | ECHS | -695.94 | 80.129 | -8.690 | 0.000 | -852.99 | -538. |

**Outcome Table 138 - Time-to-Completion: Bachelor's (t2c_bach)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: t2c_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | -128.68 | 77.202 | -1.670 | 0.096 | -279.99 | 22.63 |
| 2009 | DCE | -141.29 | 99.603 | -1.420 | 0.156 | -336.51 | 53.92 |
| 2008 | ECHS | -647.04 | 176.586 | -3.660 | 0.000 | -993.14 | -300. |
| 2009 | ECHS | -191.03 | 116.502 | -1.640 | 0.101 | -419.37 | 37.31 |

**Outcome Table 139 - High HE Degree: Associate's (high_he_degree_assoc)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: high_he_degree_assoc**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.04 | 0.052 | 0.760 | 0.449 | -0.06 | 0.14 |
| 2009 | DCE | 0.08 | 0.051 | 1.610 | 0.106 | -0.02 | 0.18 |
| 2008 | ECHS | 0.06 | 0.104 | 0.580 | 0.564 | -0.14 | 0.27 |
| 2009 | ECHS | -0.01 | 0.079 | -0.140 | 0.892 | -0.17 | 0.14 |

**Outcome Table 140 - High HE Degree: Bachelor's (high_he_degree_bach)**
**Underrepresented Student Population: Low Income Female**
**Treatment Effects Estimation: ATET** | **Treatment Model: logit**
**Outcome Model: matching** | **Outcome Variable: high_he_degree_bach**

| Cohort | Treatment | Coefficient | AI Robust Standard Error | *z* score | *P*>\|*z*\| | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| 2008 | DCE | 0.10 | 0.051 | 1.870 | 0.061 | 0.00 | 0.20 |
| 2009 | DCE | 0.06 | 0.045 | 1.310 | 0.192 | -0.03 | 0.15 |
| 2008 | ECHS | 0.15 | 0.092 | 1.600 | 0.109 | -0.03 | 0.33 |
| 2009 | ECHS | 0.13 | 0.074 | 1.740 | 0.081 | -0.02 | |

# APPENDIX N

# DATA ANALYTICS AND OUTPUT STRUCTURES

With the data files scrubbed, organized, and collapsed in such a manner as to be useful in the Propensity Score Matching analytic framework, the focus of data development turns to structuring the equations to support an examination of the targeted outcomes. The preferred data package for this study is STATA 13, which package includes a Propensity Score Matching function based on a treatment effects structure such that the average treatment effect (ATE) can be differentiated from the average treatment effect on the treated (ATET). STATA allows for the use of probit or logit estimations through the Propensity Score Matching analytic framework via a nearest neighbor match and further allows adjustments to be made for the level of match. Given the high number of observations in this data set, the nearest-neighbor matching of one observation having participated in selected treatment was matched with one observation without the treatment selection and it was not necessary to adjust the nearest neighbor match parameters. As previously indicated, both probit and logit analytic forms were employed in the study dependent on the form of the outcome variable ($Y$). Finally, STATA automatically tests for violations to the Propensity Score Matching assumptions outlined by Rosenbaum and Rubin (1983).

The STATA command structure for Propensity Score Matching is

$$teffects\ psmatch\ (Y)\ (t, X\_1, X\_2, \ldots, X\_N, form), options \qquad \text{(N.1)}$$

where $Y$ is the outcome variable, $t$ is the treatment variable, $X_1$ through $X_N$ are the pretreatment matching variables, $form$ is the preferred estimation form (logit is the standard default), and $options$ include a choice of ATE, ATET, etc.[89]

For this study, I explored a variety of command structures and examined their outcomes before choosing settling on the default nearest neighbor setting, average treatment effects on the treated, and probit or logit analytic structures (as appropriate based on the structure of the outcome variable [$Y$]). The ultimate selection of the form described was due to its methodological appropriateness rather than due to it providing superior results.

I also explored using different combinations of the pretreatment matching variables. The *race* variable consists of values for seven possible ethnicities where the *minority* variable allows for separating the population based on White and non-White. The use of the *race* variable then results in a more complex match structure and risks having an insufficient number of matches where there may not have been a sufficient number of students of a given ethnicity, which problem may be overcome by the use of the more general *minority* variable. Due to the high number of observations in the data set, the *race* variable offered no more match problems than did the *minority* variable such that there were no matching violations with the use of either variable.

Further exploration included the use of different pretreatment matching variables which resulted in violations of the matching assumptions when the variable is

[89] STATA 13 allows for a wide range of options when using the teffects psmatch command, most of which are not relevant to this study and are not referenced. A comprehensive discussion of the STATA command structure is available through the Social Science Computing Cooperative at http://www.ssc.wisc.edu/sscc/pubs/stata_psmatch.htm

representing a student's participation in a special education program while in Utah public education. As such, this variable was not included in the final matching variable list structure.

**Interpretation**

*General student population*: Interpretation of the output from Propensity Score Matching is similar to that of other uses of probit or logit, with two exceptions: 1) Propensity Score Matching estimates statistical significance based on the calculation of a $z$ score rather a $t$ statistic as explained in Chapter 3: Methodology, and 2) the estimation method does not produce an $r$ squared value to suggest a goodness of fit or how completely the model explains the outcome (Austin, 2011; Peikes, Moreno, & Orzol, 2012). If the outcome is continuous, the effect of treatment can be estimated as the difference between the mean outcome for treated subjects and the mean outcome for untreated subjects in the matched sample (Rosenbaum & Rubin, 1983). If the outcome is dichotomous (binary), the effect of treatment can be estimated as the difference between the proportion of subjects experiencing the event in each of the two groups (treated vs. untreated) in the matched sample.

The following offers an example of the output resulting from Propensity Score Matching. In this case, the 2008 High school graduation cohort is examined for the average treatment effect on the treated (ATET) of Dual-Credit Enrollment (dce_only) using a probit estimation style. The prematching variables are *k12_ever_low_income, k12_ever_ell, k12_ever_mobile, race, gender, crt_algebra, crt_science_8, and crt_language_arts_8*.

```
. teffects psmatch (k12_graduated) (dce_only  k12_ever_low_income k12_ever_ell,
k12_ever_mobile  race gender crt_algebra crt_science_8 crt_language_arts_8,
probit), atet


Treatment-effects estimation                     Number of obs      =     27033
Estimator      : propensity-score matching       Matches: requested =         1
Outcome model  : matching                                       min =         1
Treatment model: probit                                         max =         5
------------------------------------------------------------------------------
             |              AI Robust
k12_gradua~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
    dce_only |
   (1 vs 0)  |   .1660969   .0062733    26.48   0.000     .1538015    .1783922
------------------------------------------------------------------------------
```

This presents with a total of 27,033 observations from which as many as 5 matches per potential matching solution are available. With a $z$ score of 26.48 and $P>|z|$ of 0.00 the resulting coefficient of .16609069 is statistically significant. The outcome variable and treatment variable are both binary, each having a value of 1 representing High school graduation and participation in a Dual-Credit Enrollment program. The interpretation of this outcome is that the average treatment effect on the treated presents with a 16.6% increase in High school graduation over those students who did not participate in the treatment.

*Underrepresented student populations:* An interpretation of Propensity Score Matching analytics for the underrepresented student populations is somewhat different than might be expected compared to the interpretation of standard regression forms. The following represents an example of the output resulting from Propensity Score Matching where the treatment variable has been interacted with one of the pretreatment SES variables, such that we're observing the average treatment effect on the treated of a particular underrepresented class in comparison to the nontreated in that same class. In this case, we're observing the effect of Dual-Credit Enrollment on females in the 2008 High school graduation cohort (dce_only_female). The *dce_only_female* variable was formed by interacting the *dce_only* variable (0,1) with a variable for *female* (0,1) as follows: *dce_only *female = dce_only_female*. We might typically expect that the control group would be males, but in this case it is nontreated females. As with the example above, we're observing the average treatment effect on the treated (ATET) using a probit style estimation where the pre-match variables are *k12_ever_low_income, k12_ever_ell, k12_ever_mobile, race, crt_algebra, crt_science_8, and crt_language_arts_8*. Notice that the *gender* variable is missing from the pretreatment variable list: not only did this return with absolute colinearity when the analytics were performed with the *gender* variable included, as would be expected, but the STATA's internal testing functions excluded the variable.

```
. teffects psmatch (k12_graduated) (dce_only_female  k12_ever_low_income
k12_ever_ell  k12_ever_mobile  race gender crt_algebra crt_science_8
crt_language_arts_8, probit), atet

note: gender omitted because of collinearity


Treatment-effects estimation                    Number of obs      =     13395
Estimator      : propensity-score matching      Matches: requested =         1
Outcome model  : matching                                      min =         1
Treatment model: probit                                        max =         6
------------------------------------------------------------------------------
--
                |              AI Robust
k12_graduated~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
----------------+-------------------------------------------------------------
--
ATET            |
dce_only_female |
      (1 vs 0)  |   .1689473   .0087405    19.33   0.000     .1518164
.1860783
------------------------------------------------------------------------------
```

This presents with a total of 13,395 observations from which as many as 6 matches per potential matching solution are available. With a *z* score of 19.33 and

$P>|z|$ of 0.00 the resulting coefficient of .1689473 is statistically significant. The outcome variable and treatment variable are both binary, each having a value of 1 representing High school graduation and participation in a Dual-Credit Enrollment program. The interpretation of this outcome is that the average treatment effect on the treated (females) presents with a 16.9% increase in High school graduation over females who did not participate in the treatment.

# APPENDIX O

# DATA PREPARATION

Prior to performing the Propensity Score Matching analytics employed in this study, the data received from the Utah Data Alliance had to be scrubbed, organized, tested and reorganized. The initial data downloads included datasets for each of the three high school graduation cohorts. These datasets included requested demographic and student performance data gathered from the Utah Data Alliance data warehouse and included a wide range of variables (see Appendix C). The initial datasets included string formatted values and required reformatting into numeric and, or date format values before being subjected to analysis. Further, each file contained redundant identifying and demographic variables, and each of the tables excepting the K12_graduation tables (2008 and 2009) included numerous observations for each student for each year.

The first phase of the data work included organizing the delivered datasets into condensed data files, including relevant variables only, formatted in such as a way as to be useful to the data package in use for the study: STATA 13 as noted in the following sections for k12_Demographics, K12_Assessment, K12_Graduation, K12_HigherEd, K12_HigherEd_Graduation, and K12_DWS.

*K12_Demographics*: The relevant identification (person_id) and SES variables (race, gender, k12_ever_low_income, k12_ever_ell, k12_ever_mobile, and k12_ever_special_ed) variables provided by UDA were imported into a separate data file titled k12_demographics for each respective cohort year (2008 and 2009) and the file was collapsed such that each file included only one observation for each unique person_id (Table 16, Appendix B).

The gender variable was converted to a binary variable (0,1) such that a value of 1 represents male (0 represents female). The variables k12_ever_low_income, k12_ever_ell, k12_ever_mobile and K12_ever_special_ed were converted to binary variables (0,1) such that a value of 1 represented a student who had at least at one point while in Utah primary or secondary education had participated in a free meal program (k12_ever_low_income), participated in an English as a Second Language course (k12_ever_ell), moved from one school to another midprogram[90] (k12_ever_mobile), and participated in a special education course. The indicator for k12_ever_low-income is taken as proxy for lower income household status when the underrepresented student populations are considered. Prior to collapsing the respective cohort year files each was checked to make sure that each person_id included the same values for the SES variables.

The race variable was converted to a logistic variable in with the following values: White = 0, Black = 1, Hispanic = 2, Asian = 3, Pacific Islander = 4, Multiracial = 5, and American Indian = 6. This variable then also formed several others race-based variables as presented in Appendix B. The data provide in the race variables are self-reported by student households in originates in the Utah State Office of Education data tables.

*K12_Assessment*: The tables representing the public education assessment scores for each member of the target cohorts included a broad range of standardized

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[90] Program in this particular case is intended to represent the grade range for which a particular school type is designed. For example, an Elementary School "program" ranges from Kindergarten to 6th grades, a Middle School from 7th through 9th, and High School from 10th through 12th grades.

tests administered between the 8th and 12th grades. There were numerous observations per person_id, one for each test administered, and the variable list was reduced to those to be used as pretreatment performance variables (crt_8th_grade_language_arts, crt_8th_grade_science, and crt_pre_algebra) and posttreatment outcome (act_composite, act_math, act_english, act_reading, act_ science). CRT[91] and ACT[92] tests and their respective scores were chosen due to the consistency with which the exams are administered (both in form and grade level) and the consistent and objective scores (results). Some students took the ACT multiple times; the scores used for the measured outcomes represent the student's highest score. Once the data in this table had been scrubbed and variables reduced to those relevant to the research questions, each observation was expanded to include a potential variable for the test type (crt_8th_grade_language_arts, crt_8th_grade_science, and crt_pre_algebra, act_composite, act_math, act_english, act_reading, act_ science) and test score. These observations were then collapsed into one observation per person_id and were tested to be certain that the number of person_id's in the k12_demographic file for the respective cohort year was consistent with the number in the k12_assessment file. Inconsistent observations were discarded.

---

[91] Criterion Reference Tests (CRT) are used by the State of Utah for state and federally mandated testing requirements. A CRT is an assessment that is based upon certain criteria, in this case the criteria being the curriculum that has been taught to students. http://36gu5d4dxary1824ba1o7kkq6uc.wpengine.netdna-cdn.com/wp-content/uploads/SchoolTutoringAcademy-Utah-CRT-Tutoring-Program-Summary.pdf

[92] The American College Testing exam is administered to each student at the end of the 11th grade in the State of Utah. Though participation is voluntary, the Utah State Legislature provides the funding for these exams, and the majority of students elect to take them.

*K12 Graduation*: The k12_graduation tables included observations for each member of the target cohorts; as such, it acted as a guide against which the k12_demographics and each of the other data files was formed. In the k12_graduation file there was only one observation for each person_id in the respective high school graduation cohorts – consistent with the expectation that each student only graduates from one high school. Though this file contained variables for the name and identifying number of each high school and school district, these weren't retained in the collapsed data file. However, the High school name and code provided an indicator against which the student's participation in the Early College High School could be assessed. During the years for which the high school graduation cohorts are being considered, Utah had only six Early College High Schools (Academy for Math, Engineering and Science [AMES]; Intech Collegiate High School; Itineris Early College High School [Itineris]; Northern Utah Academy for Math, Engineering and Science [NUAMES]; Success Academy [Success]; and Utah County Academy of Sciences [(UCAS]). A variable (echs_ind) was formed with a value of 1 for those students who graduated from these high schools.

Additionally there were variables indicating the completion code, status and type for each student, which described a range of completion outcomes, as well as a binary indicator representing whether or not the student graduated from the high school, which graduation status met the standard used by the State and Federal governments for other education reporting mechanisms. The only one of these completion code variables that was retained in the collapsed data files was the binary graduation status indicator (k12_graduated_ind) in which 1 represents graduated; also kept was the high school completion date (exit_date). Those observations for which there was not an appropriate value in the binary graduation status indicator were discarded.

*K12 HigherEd*: The k12_highered tables included observations for each member of the target cohorts who enrolled in Utah higher education; they do not include any data for Utah higher education participants who did not attend Utah public education. Each of the respective high school graduation cohort's data files potentially contained numerous observations for each person_id, as each observation reflects each semester or term enrollment each student experienced in Utah higher education. Each observation included variables for the school (name and code), enrollment type, status and date, cumulative GPA, and cumulative credit hours, and AP and CLEP credits earned and transferred. The variables relevant to this study include the enrollment entry date (he_entry), cumulative GPA (cum_gpa) and credit hours (cum_credit_hours), transfer (credits_trans), AP (credits_ap), and CLEP credits (credits_clep) [93], and student type code and description (student_type_code and student_type_description).

It is the student type code and description that provide the definitive basis for which the Dual-Credit Enrollment and Early College High School treatments are measured. These variables reflect the type of course for which the student is enrolled (concurrent enrollment [CC), dual-credit enrollment [DC], Early College High School [EC], and regular [R and null]) for which concurrent and dual-credit enrollment were tested

[93] The cumulative GPA and credit hour variables exhibited inconsistent values upon examination and could not be used for this study at this time. These values are being researched and their consistency and reliability may be improved upon in the May 2014 data delivery from USHE, but until they are tested and deemed consistent and reliable they remain an issue for future research and study.

and found to be enrollments at the traditional high school locations and as such, formed the variable dce_only to represent Dual-Credit Enrollment when dce_only is equal to 1. The Early College High School variable (echs_only) was informed as the student_type_code is equal to EC, for which echs_only is set equal to 1.

In an effort to isolate the effects the two treatments (Dual-Credit Enrollment and Early College High School) have on the student population, each variable is considered independently (dce_only and echs_only) and collectively (dce_general) as discussed in in Chapter 3: Methodology. As a test to confirm the accuracy of the student type code indicating Early College High School, the values for echs_ind in the k12_graduation data file and echs_only in this file were compared and found to be consistent with a margin of error of less than 3%. As such the echs_only variable is used to inform a student's participation in the Early College High School treatment for this student. An overview of the counts for each of the treatment variables, both separate and combined, is found in Appendix B.

The k12_highered table also contains a variable indicating the students' higher education degree intentions. However, the entry into this variable appears inconsistent and is deemed unreliable for the purposes of this study at this time. The k12_highered tables were converted to data files prior to collapsing in order to identify the earliest and latest enrollment dates and types in the tables. Once these were identified, their values were stored and the files were collapsed into data files titled highered20__ for each respective cohort year.

*K12 HigherEd Graduation:* The k12_highered_graduation data tables for the respective high school graduation cohorts include detailed higher education graduation data only for those students who both participated in Utah secondary and higher education, but also graduated from Utah higher education. This table potentially includes numerous observations for each person_id as some students experience higher education graduations at the Certificate, Associate's, Bachelor's, and Master's Degree levels. There were no students in the study's respective cohort years that completed a PhD level education.

While this data table included variables for degree type and code (he_degree_type, he_degree_code), higher education graduation date (grad_date), higher education institution name and code (institution_name, institution_code), CIP code and description (cip_code, cip_description) and indicators for Utah higher education enrollment (ushe_ind) and Utah higher education graduation (ushe_grad), the institution and CIP name, code and description variables were not maintained for this study. Variables for each potential higher education graduation were formed for each observation (he_degree variables 1-6; there were no observations with more than five higher education graduations) and the files were collapsed into respective high school graduation cohorts with unique observations for each student (person_id).

It's worth noting that it is the k12_highered and k12_highered_graduation files that are likely to experience meaningful change in the May 2014 data download from USOE, USHE, and UT DWS, sufficient to warrant recalculation of all variable values and outcomes. An examination of the unique person_id observations for k12_highered_graduation data files reveal as of the current data release (May 2013) shows the following numbers of students having earned various higher education degrees: 2008 = 5471, 2009 = 3459 and 2010 = 2295. As would be expected, the number declines sharply with each high school graduation cohort year and would be expected to do so until each of the cohort has passed the 6-year high school graduation anniversary.

*K12 DWS*: The k12_dws data tables for the respective high school graduation cohorts reflects Utah Department of Workforce Services data, and while the datasets represent a rich data source, availability of workforce data for the respective cohorts with sufficient detail as to provide a useful addition to this study, it is sufficiently limited as to exclude its use in this study. Not only has there been an insufficient amount of time between potential higher education graduation to provide useful results, but the state of the US and Utah labor markets in the years since high school graduation (2008 and 2009) have been marked with a high level of unemployment and labor market uncertainty. These data will likely be considered for future study.

*UDA Merged:* Once the respective data files are collapsed and tested for completeness they're merged to form a single data file for each high school graduation cohort with unique observations for each student (person_id); with the exception of the k12_dws data files as previously noted. Though representative of several different datasets and observations for each student taken at various points in their Utah public secondary and higher education careers, these files form a cross sectional data file reflective of the relevant aspects of the student's experience in respect to the aims of this study and given the available variables. After the data files are merged a variable representing the cohort year is added to each of the respective files (2008 and 2009) and the files are then merged into one master file in panel data form with unique observations for each student (person_id) in their respective high school graduation cohort years. This file is exposed to a final testing for duplicate person_id's in and across cohort years and any duplicates are either resolved or discarded based on completeness. The final tabulation of the data files is reported in Appendix B.

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